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Research on Power Efficiency and Key Technologies of Non-linear MIMO for Internet of Vehicles

by

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Certificate of Authorship/Originality

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Dedication

This thesis is dedicated to my parents.

This stands as a testimony for their endless support and love.

To my supervisors, for the academic guidance.

To my friends, for their encouragement.
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I have to start by thanking my perfect parents Jiamin Gong and Junhua Xu. They bring me to this fantastic world, support me to pursue research, allow me to be myself. Many Thanks!

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List of Publications

Published Journal Papers


Published Conference Papers


**Patents**


ABSTRACT

Research on Power Efficiency and Key Technologies of Non-linear MIMO for Internet of Vehicles

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“Green new infrastructure” is an essential part of the new round of global technological and industrial revolution. It has become an “accelerator” supporting the transformation and upgrading the performance of the industrial structure. The Internet of Vehicles (IoV), as one of the essential landing application scenarios of the “new infrastructure” project, is a communication network for supporting vehicle and transportation applications. Through massive connections and collaborative computing of the humans, the vehicles, and the road infrastructures, the IoV can enhance the sensing range of vehicles and realize the interconnection of people-vehicle-road-cloud. The IoV deploys a large number of infrastructures with communication capabilities in cities, including the Fifth-generation (5G) base stations, sensors, roadside units, etc. Considering the problem of reducing the energy consumption of infrastructure in the IoV, the works of this thesis are mainly listed as the following:

- Considering the challenges brought by the V2V channel model in cities, the method of modelling V2V channels based on real geographic location information and vehicle driving environment information is studied. A real-time V2V channel model based on real geographic location information is proposed.

- The structure design of the non-linear receiver for IoV communication was studied to address the problem of excessive-high power consumption in the IoV. The non-linear low-power radio frequency (RF) receiver structure was
proposed based on replacing the intermediate-frequency and high-frequency parts contained in the conventional receiver with an amplitude or phase-detection receiver. The approach for deploying low-power non-linear RF receivers on infrastructure in urban environments, such as 5G base stations, roadside units, communication nodes, sensor networks, etc., to form a green and low-power IoV’s ecosystem were also presented in this thesis.

- In view of the challenges imposed by the capacity of non-linear MIMO in the IoV, a method for calculating the uplink achievable rate of non-linear MIMO systems is proposed using the mutual information theory. While deriving the general calculation framework, an efficient Antithetic-quasi Monte Carlo algorithm is proposed, which effectively solves the problem of high-dimensional integration.

- In response to the non-linear MIMO receiver’s challenges in IoV, the Expectation-Maximum (EM) algorithm based on the Gaussian Mixture Model (GMM) is used to solve the channel estimation and multiuser detection problem under the -phase observations. Based on the proposed framework, the GMM-type channel estimator and multiuser detector are designed for HPO-MIMO.
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Abbreviation

3GPP : the 3rd Generation Partner Project
4G : 4th Generation
5G : 5th Generation
6G : 6th Generation
ADC : Analog to Digital Converter
AMP : Approximate Message Passing
BLER : Block Error Rare
CE : Channel Estimation
CP : Cyclic Prefix
CPM : Constant Phase Modulation
D2D : Device to Device
DSRC : Dedicated Short Range Communication
EM : Expectation-Maximum
FSK : Frequency Shift Keying
GAMP : Generalized Approximate Message Passing
GPS : Global Position System
GMM : Gaussian Mixture Model
GWV2V : Geometry Enhances Winner II V2V
HPO-MIMO : Half Phase Only-MIMO
I/Q : In-phase/Quadrature
IIoT : Industry Internet of Things
IoT : Internet of Things
IT : Information Technology
ITS : Intelligent Transportation System
IoV : Internet of Vehicles
ITU : International Telecommunication Union
I2I : Infrastructure-to-Infrastructure
LOS : Line of Sight
LNA : Low Noise Amplifier
LTE : Long Term Evolution
MC : Monte Carlo
MUD : Multiuser Detection
MIMO : Multiple-Input Multiple-Output
MANET : Mobile Ad-hoc Network
MO-MIMO : Magnitude Only MIMO
NLOS : None Line of Sight
NLOS-V : None Line of Sight caused by Vehicle
NLOS-B : None Line of Sight caused by Building
OOK : On-Off Keying
OBU : On-Board Unit
OSM : OpenStreetMap
PLL : Phase-Locked Loop
PO-MIMO : Phase Only MIMO
QMC : Quasi Monte Carlo
RF : Radio Frequency
RSU : Road Side Unit
SNR : Signal Noise Ratio
SISO : Single-Input Single-Output
SD : Sphere Decoding
UWB : Ultra Wide Band
V2P : Vehicle-to-Pedestrian
V2V : Vehicle-to-Vehicle
V2I : Vehicle-to-Infrastructure
V2N : Vehicle-to-Network
VANET : Vehicular Ad-hoc Network
Chapter 1

Introduction

In the past few decades, transportation demand has snowballed, and the construction of transportation infrastructure has fallen far behind the growth of transportation demand, which directly affects social and economic development. At present, “green” is the primary concern of infrastructure construction related to environmental protection, energy-saving, green transportation, green buildings, etc. Therefore, this thesis focuses on adopting new technologies to improve the transportation system’s operation efficiency and improve the existing transportation system’s existing defects. Various countries have proposed a green, sustainable and intelligent transportation system. In order to promote and expand the research of the future green “new infrastructure”, it is necessary to put forward new technologies, new theories, and new methods in this field and provide theories for building a sustainable green IoV ecosystem. European countries first proposed the concept of “green IoV”, and its concept mainly focused on green transportation. The modern “green IoV networking ecosystem” is a brand-new concept, adhering to the concept of sustainable development in environmental issues, and emphasizing the “greenness”, “intelligence,” and “creativity” of urban traffic, which is helping to reduce traffic congestion and reduce environmental pollution. The requirements for promoting the rational use of resources by society are very prominent.

1.1 Background

At present, the Internet of Vehicles (IoV) research has laid a technical foundation for developing the green IoV ecosystem. The IoV utilizes radio frequency identifi-
cation technology to manage vehicles, including real-time tracking and monitoring vehicle operating conditions. Like the Internet of Things (IoT), the foundation of the IoV relies on the deployment of a large number of sensors to integrate information gathered from base stations (BS), roadside units (RSU), and roadside infrastructure to form an “interconnection” between cars and roads. By cooperating with the road and technology management departments, the communication between moving vehicles, roads, and pedestrians could be realized, and the green IoV ecosystem can be indeed implemented.

However, on the one hand, with the increase of roadside infrastructure, the number of sensors that need to be deployed will rise sharply. On the other hand, with the 5G commercial period’s coming, a huge number of 5G base stations will be deployed, which consume more power than traditional base stations. The 5G base stations use millimeter-wave MIMO [1] [2] [3] [4], massive MIMO technology [5] [6] [7] [8], which needs more than 100 antennas on each BS side [9] [10]. The number of base stations will show exponential growth in the next five years (as shown in Figure 1.1).

![Forecast of the number of 5G base stations (ten thousands)](image)

Figure 1.1 : Forecast of the number of 5G base stations (ten thousands).

Therefore, designing energy-saving and emission-reducing “new infrastructure”
to help RSU obtain all kinds of city information to achieve the national new infrastructure strategic planning goals, which poses a significant challenge to constructing a green IoV ecosystem. The following first introduces the related technologies of the IoV and their different application scenarios and then introduces the main solutions for the current realization of the green IoV ecosystem under different application scenario analysis.

1.2 Internet of Vehicles related technologies and challenges

The IoV is one of the typical applications of the current Internet of Things (IoT) technology. In IoV, vehicles expand human behavior by interacting with data to provide services for drivers and users. With the development of communication technology in IoV, Intelligent Transportation System (ITS) has been widely used as an important part of IoV. ITS provides safer, more effective, and lower-latency services through information interaction between vehicles and infrastructure to achieve effective resource utilization. Moving vehicles obtain environmental data from billions of sensors or node devices in IoV and make reasonable judgments and decisions. From the driver’s perspective, it helps the driver optimize and adjust the driving route in real-time according to the actual traffic conditions and predicts some potential risks leading to traffic accidents in advance, and activates the early warning mechanism of the IoV communication system. Reduce and avoid traffic accidents so that the life and property safety of drivers and passengers are guaranteed.

However, ITS depends on whether the driving vehicle can quickly and effectively collect data from the sensors and communication nodes in IoV. Therefore, researchers need to consider the communication node’s coverage and consider the business’s needs requires high reliability, such as in-vehicle entertainment services. To further reduce traffic accidents and improve traffic efficiency, people combine wireless communication technology with traffic systems to form a Vehicular Ad-
The concept of VANET was first proposed in 2003. It is a special application of the Mobile Ad-hoc Network (MANET) in vehicle networks [11] [12] [13] [14]. Specifically, VANET is a dynamic mobile network oriented to vehicle communication services. As shown in Figure 1.2, vehicles traveling in cities and roadside infrastructure are the main elements in VANET. Each vehicle is equipped with an on-board Unit (OBU) with a communication function. The function of the on-board unit is to exchange information with surrounding vehicles or roadside infrastructure. The city’s infrastructure includes roadside units (RSU) built on both sides of the road. The role of the RSU is similar to the OBU, which exchanges information with surrounding vehicles or other RSU. This information includes vehicle speed, road congestion, traffic accident location, and road surrounding environment information.

The IoV extracts and processes the dynamic information from the driving environment to realize the information sharing among driving vehicles [15]. According to the different communication subjects, the IoV can be divided into three
scenarios [16]. Vehicle-to-Vehicle (V2V) communication [17] [18] [19], Vehicle-to-Infrastructure communication (V2I) [20] [21], and Infrastructure-to-Infrastructure communication (I2I). The three communication scenarios in IoV are introduced in detail in the following.

1. Vehicle-to-Vehicle (V2V) communication model

Figure 1.3 shows the V2V communication model. As shown in the figure, moving vehicles can obtain road information and data transmission by loading OBU. Communication vehicles moving on the road have the characteristics of high speed and low delay. Vehicles within a specific range can freely consist of a scalable network structure. In this network, vehicles generally use Dedicated Short Range Communication (DSRC) technology. However, due to the vehicle’s high speed, there is no relatively stable speed between the vehicle pairs, making the network in this scenario unstable [22]. Besides, since both ends of the communication are high-moving vehicles, the original base station-mobile terminal channel is no longer suitable for vehicle scenarios. The application scenarios of V2V communication include: assisting vehicles in changing lanes, assisting traffic merging, assisting in detecting blind areas, forward collision warning, etc., in helping drivers predict vehicle conditions and avoid accidents caused by blind regions.

2. Vehicle-to-Infrastructure (V2I) communication model

Figure 1.4 shows the communication model between vehicles and roadside infrastructure. The roadside infrastructure includes traffic lights, various types of traffic cameras, roadside units, etc. As shown in Figure 1.4, high-speed vehicles and roadside infrastructure exchange two-way information and data. Similar to V2V communication, DSRC technology is often used in V2I scenarios, but unlike V2V, where both ends are mobile vehicles, the roadside infrastructure in V2I scenarios is fixed at a specific location and has the feature of immovability. Therefore, the
network of V2I is not as stable as V2V, but its channel characteristics are similar to the traditional BS-mobile UE. The traditional communication channel can be used for reference only by considering the mobile terminal’s high-speed characteristics. The application scenarios of communication between vehicles and roadside infrastructure include: pre-judgment warning of road congestion ahead, warning of dangerous road ahead, traffic light information prediction, crossroad collision warn-
ing, warning of frequent accident areas, and intelligent management of electronic
toll stations at highway intersections, etc. These communication scenarios help the
driver predict the travel path and driving behavior, reduce travel time, and improve
driving efficiency.

3. Infrastructure-to-Infrastructure communication (I2I) model

Figure 1.5 shows the I2I communication model between roadside infrastructure
and roadside infrastructure in IoV. The communication between roadside infrastructures can achieve a broader range of information sharing. The application scenarios of communication in I2I include early warning of distant traffic accidents, updating real-time messages, etc. [23].

Figure 1.5: Infrastructure-to-Infrastructure (I2I) communication structure.

With the gradual commercialization of the current 5G communications, 5G base
stations play an important role in IoV. From the perspective of forwarding information, 5G base stations are similar to traditional BS and can be used as relays to connect various elements in IoV. At the same time, 5G can also be regarded as a roadside unit to replace the traditional roadside unit and improve economic effi-
ciency. Since 5G BSs deploy more antennas than traditional BSs, such as massive MIMO and millimeter-wave MIMO, 5G BSs have higher accuracy than traditional BSs in terms of vehicle positioning.

Figure 1.6: 5G IoV structure.

Figure 1.6 shows the 5G IoV communication scenario [24]. It can be seen that the 5G BS is characterized by the use of a large-scale antenna array. The entire 5G IoV can be divided into intra-vehicle networking, inter-vehicle networking, and in-vehicle mobile Internet. For the intra-vehicle networking, the 5G in-vehicle OBU and the 5G mobile terminal can be interconnected, that is, the interconnection between the vehicle and the pedestrian (Vehicle-to-Pedestrian, V2P) is realized; in the inter-vehicle networking, the communication between the V2V is used to realize the self-organizing communication between vehicles; in the in-vehicle mobile Internet, the 5G BS can act as a relay to provide services for the interconnection in
The 5G IoV realizes the interconnection and intercommunication between the intra-vehicle networking, inter-vehicle networking, and the in-vehicle mobile Internet. Compared with the current IoV, the connectivity has been further improved. However, in the 5G IoV communication scenario, the massive amount of data generated by 5G technology causes excessive power consumption, resulting in excessive power consumption of the overall Internet of Vehicles system. In this scenario, how to achieve the goal of low energy consumption, energy-saving, and emission reduction in green IoV has become a hot topic.

According to the above introduction, there are two challenges in the current IoV. Firstly, there is a lack of a channel model that meets the characteristics of V2V in IoV, and the channel model is the basis of communication system design. Otherwise, this problem is the first problem to be solved in IoV. Secondly, the characteristics of V2V communication include time delay, multipath fading, and Doppler frequency deviation, which all depend on the surrounding environment and relative speed of the moving vehicle. Compared with the traditional base station-mobile terminal communication scheme, V2V communication has the following new features [25]:

1. A radio signal from the transmitter can be easily obstructed by buildings and large trees due to the low terminal height of a vehicle.

2. Since the transmission scenario is highly sophisticated, radio waves will be reflected many times, and abundant signals occur such as in the case of a road surrounded by several tall buildings.

3. Due to the high speeds of vehicles, Doppler spreading will be considerable.

4. Changes in the environment render wireless channels unstable and affect the propagation of a signal and channel responses, producing time-variant properties characterizing the channels.
Secondly, with the gradual implementation of “new infrastructure” and commercial construction of 5G base stations, the number of sensors that need to be deployed and the number of 5G base stations with huge power consumption have risen exponentially. How to achieve the goal of low energy consumption, energy-saving, and emission reduction in the green IoV in this scenario has become a problem that must be solved. At present, three indicators affect whether the green IoV reaches the target of “green” [26]:

(1) Fuel consumption and emissions of vehicles:

Although there is no need to consider the power consumption of fuel vehicles, petroleum-based vehicles will still cause carbon dioxide emissions, leading to global warming. Besides, as the global economy changes and fuel prices have risen sharply, attention should be paid to avoid excessive fuel consumption from an economic point of view. Therefore, even fuel vehicles should consider traveling as low as possible.

(2) Power consumption:

In the past ten years, some automakers have introduced electric vehicles and hybrid electric vehicles into the market, and their penetration rates have continued to increase worldwide [27]. So far, as an essential element, electric vehicles are the first to be included in the discussion of the green IoV [28] [29]. Therefore, due to the battery limit, electric vehicles should also consider how to achieve interconnection in IoV with less power consumption from the communication perspective [30].

(3) Communication overhead:

In IoV, the type of wireless communication system determines its power consumption level. For example, in a cellular system, the base station does not need to consider its power consumption, while cellular users are limited by their power. However, in the 5G and the future 6th Generation (6G) network system, due to the use of massive MIMO and millimeter wave technology, the power consumption of
the base station has turned into a problem that must be considered [31]. Besides, due to the massive deployment of sensors and communication nodes, self-organizing networks and wireless sensor networks need to pay attention to the overall network’s power consumption. The current IoV technology is combined with wireless sensor networks, 5G, and future 6G technologies. Therefore, how to reduce the power consumption of the IoV with the introduction of a large number of sensors and a large number of 5G/6G base stations is a problem that must be solved to realize the vision of the green IoV.

In view of the two aspects mentioned above of the IoV, this thesis will focus on the current research works and existing above problems.

1.3 Relative works

1.3.1 Relative works on wireless channel model for Internet of Vehicles

As an essential part of the physical layer in IoV, wireless channels have always attracted attention. In the V2V communication scenario, vehicles as the transceiver are limited to moving on the road and with high mobility characters. Based on these characteristics, traditional cellular communication system channels’ research results are no longer suitable for V2V communication scenarios. Therefore, exploring wireless channels’ characteristics in the IoV environment and studying the transmission characteristics of wireless signals at the on-board transceiver will help design the IoV communication system.

Akki and Haber [32] first proposed a V2V Rayleigh fading channel model for narrow-band isotropic scattering single-input and single-output (SISO) in 1986. The research on intelligent communication between vehicles began to gradually enter the discussion and testing stage in 1999 [33] [34]. Since the 21st century, research has found that compared with SISO technology, multiple-input and multiple-output
(MIMO) technology can effectively improve channel reliability and system capacity [35]. For intelligent communication between vehicles, vehicles have the advantage of installing multiple antenna systems (such as on the top of the vehicle). Therefore, MIMO technology has great research value in the field of vehicle networking V2V communication. With the increasing global demand for smart cars and the rapid development of IoV technology, the research on the V2V wireless communication channel has also attracted more scholars’ attention. In recent years, the research on the V2V communication system’s channel model has achieved many theoretical results. According to the different modeling methods, it can be divided into the following categories:

1. Statistical Model

Previous studies are mainly based on some typical statistical channel models. Such models include WINNER II type, WSSUS type, and LEE type. Their advantage is that the model is simple, and modeling can be completed only by analyzing the statistical characteristics of the channel’s angle spread and delay spread. However, because these models do not provide information such as the driving environment, they cannot reflect the real driving scene’s channel environment.

Such as [36], the three V2V statistical models mentioned are established based on the small-scale characteristics of different communication scenarios in six cities. Since the three parameters concluding vehicle distribution density, moving speed, and driving route in the model cannot be dynamically adjusted, it does not show good adaptability to different moving scenes. The parameters commonly used in IoV and some typical scenes of macrocells in cities are fully defined and described in the literature [37]. The Channel model established in [38], for the non-stationarity of the vehicle networking channel, although the ability to affect the traffic density parameters and the appearance and disappearance of taps is considered. However,
this model not only fails to reflect the continuous movement of the scatterer in different paths, but also the Doppler frequency offset cannot accurately show the line of sight (LOS) path with obvious frequency components, which is contrary to the real world.

2. Certain Model

For different communication scenarios, the certain model obtains specific physical parameters to ensure the practicality and accuracy of the model. Solving Maxwell’s equations in a specific discrete manner can obtain precise important parameters at instants time, and ray tracing [39] can also be used to obtain approximate important parameters. It is not difficult to find that the results obtained by the accurate model are very sensitive and often get different values for different environments. The physical characteristics and orientation of obstacles in the environment have become an important part of the results, which guide the transmission process of reproduced electromagnetic waves. Accuracy is the biggest advantage of this model. It is completely imitated and adds a variety of situations that may occur in real-world modeling. The ability to describe the specific environment in detail, the higher complexity, and the calculation time have become the most obvious shortcomings, and the unique scenes are difficult to replicate. Finally, for time-varying channels, the process of obtaining a large number of parameters using certain modeling methods has certain complexity and challenges.

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characteristics and orientation of obstacles in the environment have become an essential part of the channel modeling, guiding significance for the transmission process of reproduced electromagnetic waves. Accuracy is the most significant advantage of this model. It is wholly imitated and adds a variety of situations that may occur in the real-world. The ability to describe the specific environment in detail, the higher complexity, and the calculation time have become the most obvious shortcomings, and the unique scenes are challenging to replicate. Finally, for time-varying channels, the process of obtaining a large number of parameters using certain modeling methods has certain complexity and challenges.

[40] [41] analyzed the fading effects changing of V2V channels in urban, rural, suburban and other environments by means of measured data, and established path loss prediction models in corresponding scenarios based on the measured data. [42] measured dynamic V2V channels at urban crossroads and overpasses, and analyzed and compared Doppler delay power in different scenarios. [41] modeled different scatterers such as antennas, vehicles, trees, buildings, and weather, and established a SISO channel model based on V2V communication according to the geometric optical mirroring method. [40] proposed a V2V channel model of the ray tracing method, through which the actual radio propagation process in a given environment was reproduced. The representation of the real environment includes two parts: the modeling of dynamic road traffic such as moving vehicles and the modeling of the roadside environment such as buildings and parked cars, and the use of geometric optics and geometric factor rules to generate possible transmission from the sender to the receiver propagation path to realize the wave propagation model.

This type of model’s characteristic is that the channel characteristics can be accurately calculated based on the specific environment, so the accuracy of this type of channel model is high. However, due to the need for specific information of the
channel in a specific environment, and the modeling process requires a large amount of calculation, the acquisition and simulation of channel data requires exceptionally high costs, which is almost impossible to achieve in practical applications.

3. Geometry-based statistical model

The Internet of Vehicles environment is extremely complex, so a channel model is needed that can describe application scenarios in different environments. According to research [43] [44] [45], the geometric-based statistical model meets this requirement. Under the basic premise of wave propagation, this model presupposes that there are effective scatterers in a specific geometric shape and then change the scattering area’s shape or the probability density function model different application scenarios.

In this model, only effective scatterers in the scene (scatterers that affect the system) are considered, not all of them. Therefore, this model is often used for theoretical analysis and research. Besides, according to the model’s shape, the model can be further subdivided into regular and irregular models, both of which have their advantages and disadvantages. For example, a regular geometric model can take advantage of geometric operations’ convenience, while an irregular geometric model can fully describe the real physical environment. Research investigations show that scatterers’ distribution in urban environments is mostly non-omnidirectional scattering, and irregular geometric models can describe non-omnidirectional scattering. This greatly simplifies the modeling of geometric certain simulation models and only effective adjustments. The statistical distribution of the position of the scatterer can be applied to various vehicular communication scenarios. In summary, geometric-based statistical models are more applicable in V2V communication scenarios than the above mentioned statistical models and certain models.

To study the real-time channel characteristics in V2V communication in real sce-
narios, literature [46] uses the map information in Google Maps to obtain real-time environmental parameters. The communication range is delineated with the sending and receiving vehicles as the focal point, and a geometry-based V2V communication channel model is established on this basis. In this model, the V2V communication link can be divided into line-of-sight paths (LOS), non-line-of-sight paths (NLOS-V), and non-line-of-sight paths caused by buildings (NLOS-B) Three types. Then the large-scale fading signal model calculations are performed on these three types, respectively. However, this model does not do too much analysis on small-scale fading and Doppler effect and only simulates a single reflection in an urban scene, which is inconsistent with the multiple reflections that often occur in reality.

1.3.2 Relative works on green Internet of Vehicles

It can be seen from the discussion in Section 1.2 that with the development of “new infrastructure” and the commercial construction of 5G base stations, in the 5G IoV scenario, the massive number of roadside units, sensors that need to be deployed, and the number of 5G base stations with huge power consumption are increasing exponentially [47]. Therefore, the primary task of achieving green and low power consumption in VANET is to reduce the power consumption of the above elements. Besides, with the popularity of electric vehicles limited by battery technology, electric vehicles’ power consumption should also be fully considered.

Generally speaking, although only two pairs of antennas are required on each roadside unit, sensor, and vehicle, the large quantity of them in the 5G IoV scenario will still lead to immense power consumption. The power consumption problem of 5G base stations is prominent because of the increasing antennas. For example, massive MIMO and millimeter-wave base stations need to equip more than 100 antennas. Each antenna needs to correspond to a radio frequency (RF) link. This link includes digital-to-analog converters, mixers, and power amplifiers with extremely
high power consumption and precision requirements. The pre-processed baseband signal is up-converted and modulated, and then transmitted through the antenna. The increase in number will inevitably lead to a substantial increase in system implementation costs and energy consumption. Therefore, whether it is for roadside units, sensors, vehicles, or 5G base stations, from the perspective of reducing the total power consumption and deployment cost of the system, the use of low-power receivers and low-precision quantitative receivers are both One of the direct ways to realize the high energy efficiency of the system effectively.

1. Low power receiver

Ultra Wide Band (UWB) [48] in wireless communication technology is essential technology of the Internet of Things (IoT). It has the advantages of higher speed, lower power consumption, and low cost, also higher spectrum utilization. It is widely used in IoV, wireless sensor networks (WSN) [49] [50], positioning, and other fields [51]. As the main part of wireless communication, the radio frequency as the part of the transceiver, also called the radio frequency transceiver, is the key factor to achieving ultra-bandwidth communication [52]. Radiofrequency receiver technology first appeared in the concept of WSN. WSN system is composed of a certain number of wireless sensor nodes. Each node can collect environmental data and transmit data through wireless communication. The system has been widely deployed and used in military, Intelligent transportation, environmental monitoring, and other fields [53].

Traditional radio frequency receiver architectures, such as the most commonly used superheterodyne receiver, are usually used in communication scenarios that require high signal quality and transmission rate. Due to the signal modulation’s complex characteristics, the receiver needs to use a high-performance and high-precision circuit [54]. The most significant feature of superheterodyne receivers is to
convert high radio frequency signals into intermediate frequency signals. Specifically, after the radio frequency signal is filtered and amplified by a filter and a low noise amplifier (LNA), the radio frequency signal is mixed with the local oscillator signal through a mixer and converted into an intermediate frequency signal. Its structure is shown in Figure 1.7.

The analog front end of the superheterodyne receiver structure contains multiple LNAs, filters, mixers, voltage-controlled oscillator (VCO), RF synchronization, and analog-to-digital converters (ADC). Besides, all hardware components in this structure need to have good linearity and high dynamic characteristics, and the phase noise needs to be controlled by a phase-locked loop (PLL). The above requirements result in prohibitive cost and high power consumption. Although technical improvements in integrated circuits will ultimately reduce cost and power consumption, the basic requirements for the two (In-phase/Quadrature, I/Q) branches cannot be avoided. Therefore, the conventional superheterodyne receiver is not suitable for the design of low-power receivers.

In IoV, where UWN and WSN technology are widely used, especially some nodes are also deployed inside the facility or in dangerous and complex environments. In this situation, it becomes essential to reduce the power consumption of the RF
receiver’s front-end circuit. Therefore, how to solve the problems of energy saving has become a critical issue that needs to be solved urgently in the current IoV [55].

Compared with the transmitter, the receiver has a more complicated structure, and the power consumption of the receiver is much higher than that of the transmitter. Therefore, it is of greater significance and value in the green wireless communication systems to study how to design low-power receivers. In addition to traditional superheterodyne receivers, zero intermediate frequency receivers and low intermediate frequency receivers have received widespread attention to reducing power consumption.

Compared with the traditional superheterodyne receiver, the zero intermediate frequency receiver [56] has the characteristic that the local oscillator signal and the radio frequency signal have the same frequency. The zero intermediate frequency receiver means that the structure directly converts the intermediate frequency to 0, so there is no interference from other frequencies. Compared with the traditional superheterodyne receiver structure, the device that suppresses the image frequency is removed, thus reducing the overall complexity and power consumption. Its structure is shown in Figure 1.8.

![Figure 1.8: Zero intermediate frequency receiver architecture.](image)
Compared with the zero intermediate frequency receiver, the low intermediate frequency receiver [57] is also a successful application. Its structure is similar to those mentioned above zero intermediate frequency receiver. The difference is that the RF signal is not directly down-converted to 0, but down-converted to a very low intermediate frequency signal. Low intermediate frequency signals have achieved some equalization between traditional superheterodyne receivers and low intermediate frequency receivers. For example, under the premise that the receiver structure is relatively simple, the power consumption can still be kept at a low level.

2. Low-resolution quantization receiver

Besides, some research works have designed the low-power, low-resolution digital-to-analog converter receiver from the perspective of digital processing data bit width, that is, from the perspective of data quantization accuracy [58] [59]. In the low-resolution receiver, the signal at the receiver side is transmitted to the quantizer through the RF channel. The in-phase and quadrature components of the input signal are respectively sampled and quantized by a pair of low-precision ADCs in the quantizer, and output to the baseband processing unit performs subsequent signal processing.

![Low-resolution quantization receiver architecture.](image)

The specific structure is to replace the accuracy of the two pairs of ADCs in the
traditional superheterodyne receiver from high-resolution to low-resolution. The structure is shown in Figure 1.9. The reason is that for the GHz order, its sampling frequency and high-resolution quantization will bring great complexity and more power consumption in baseband processing. For example, the sampling frequency of an 8-bit resolution ADC is about 10GHz, its power consumption is more than thousands of milliwatts, and one piece’s cost is as high as several hundred USA dollars. Therefore, the low-resolution ADC receiver can effectively save hardware costs while ensuring a significant reduction in power consumption. [60] analyzes the channel capacity of low-precision 1-bit quantized MIMO when the transmitter perfectly knows the channel state information. [61] [62] constructed a channel estimator and a multi-user detector for low-precision quantization schemes based on convex optimization ideas and approximate message passing algorithms, and verified their effectiveness through theoretical analysis and experimental simulation.

Both of the above two solutions can significantly reduce the power consumption on each RF link and solve the problem of excessive power consumption at the receiver side from the hardware perspective. However, when the receiver uses zero intermediate frequency and low intermediate frequency, it can be observed that two corresponding ADCs are still needed from those structural representations in Figure 1.8 and Figure 1.9. Because the above two structures still use IQ modulation, the overall RF link power consumption is still too high. Besides, in the low-resolution quantization receiver solution, compared to the high-resolution ADC, the low-resolution ADC’s quantization accuracy becomes smaller, and the quantization error problem becomes non-negligible. Due to the internal structure of the ADC, the quantization error is a more complex nonlinear error. Therefore, under this scheme, there existing the problems caused by the IQ modulation as mentioned above and the problem of quantization errors caused by low-precision quantization.
1.3.3 Problems in existing relative works

As far as the analysis of the current works, the green IoV ecosystem’s investigation is still incomplete. In many fields, further research and improvement are still needed, and there is still a long way to go to meet the application of actual urban environment scenarios. Based on existing works, the shortcomings and challenges are mainly concentrated in the following four aspects:

1) For the V2V communication in urban scenarios, a novel V2V channel model that meets the real driving environment is urgently needed. Unlike the traditional wireless communication channel model between the base station and terminal, V2V communication faces the problem of mobility at both ends, and the surrounding driving environment will change rapidly with the vehicle’s moving. Traditional cellular wireless channel studied in the past is no longer applicable. Therefore, V2V channel modeling based on real geographic location information and vehicle driving information is a critical issue that needs to be solved first.

2) Facing the green IoV, not only communication vehicles and base stations are required to save energy, but also those communication devices that are limited by batteries in an urban environment are required to focus on the low energy consumption characteristics. Although existing low-power receivers reduce power consumption in some ways, their essence is still I/Q modulation, that is, two ADC links are required, and there are complex structures and high power consumption. Therefore, designing a low-complexity and low-power receiver in the green IoV has become a problem that must be notable.

3) The key to using ultra-bandwidth technology and wireless sensor network technology to achieve the establishment of an urban green IoV is how to use the large number of low-power receivers deployed in roadside units, communication nodes, 5G base stations, and various sensors. However, no matter what kind of
low-consumption receiver, some information will inevitably be lost, leading to decreased system performance. After the low-power receiver has undergone non-linear distortion, its physical characteristics have changed and no longer have traditional receivers’ characteristics to receive I/Q signals. Specifically, there is no closed-form solution like traditional receivers when calculating their system capacity. Therefore, it is necessary to analyze the non-linear MIMO system’s achievable rate composed of a non-linear low-power RF receiver to observe whether those structures can still achieve the same capacity requirements as traditional MIMO while reducing power consumption.

4) Equipped with non-linear low-power receivers in the form of MIMO on vehicles and urban infrastructure, including 5G base stations, roadside units, and communication vehicles, aiming to solve the problem of excessive power consumption in IoV. However, unlike the traditional MIMO baseband algorithm, the receiver side’s signal has undergone non-linear distortion, and the complete amplitude and phase of the received signal cannot be observed. Therefore, the traditional baseband algorithm is no longer applicable, so how to reconstruct the transmitted signal under the observation of only amplitude or phase of the signal has become a problem that must be solved.

1.4 Thesis Contributions and Organization

This thesis is based on the research results of 3 journal papers and 3 conference paper.

1.4.1 Thesis contributions and innovations

This thesis will comprehensively apply relevant knowledge such as information theory, stochastic theory, optimization theory, data structure theory, and simulation modeling based on the current research works. Focusing on green energy-saving
characteristics, based on the real-world urban scenario, combined with non-linear MIMO technology to conduct in-depth research in the IoV, and strive to promote the application of “green new infrastructure” in smart cities.

This thesis is mainly divided into four contents: the first research content is based on the real geographic location information and the vehicle driving environment information to model the V2V channel in the urban environment; the second research content is the low-power receiver design for the green communication in IoV; the third research content is the achievable rate analysis of the non-linear MIMO technology for the IoV; the fourth research content is the design of the non-linear MIMO channel estimation and the multi-user detection algorithm for the IoV. The research content and corresponding main contributions are summarized as follows:

(1) Geometry Enhanced Winner II Channel Model based on real city geographic location information

In response to challenge 1, this thesis uses various communication nodes deployed in the city to obtain urban environmental information and vehicle driving information and combines specific scenarios to propose a real-time V2V channel model based on real geographic location information. Furthermore, according to the Third-Generation Partnership Project (3GPP), a link-level simulation platform suitable for Long Term Evolution (LTE) V2V is built. When building the V2V channel model, the real geographic location information is used to construct the large-scale fading model, and the surrounding environment location information of the communication vehicle is used to construct the small-scale fading model. The Doppler effect is measured by obtaining the relative speed of the two communication vehicles. When judging the link type of communication vehicle pairs, geometrical methods are used to analyze multiple interactions between vehicles such as reflection and diffraction, and an R-tree structure is proposed to improve the efficiency
of search and judgment. The proposed channel model solves the problem which the channel model does not fit the real-world environment in the current vehicle networking environment.

(2) Structure Design of Power-efficiency Non-linear Receiver for the Internet of Vehicles

In response to challenge 2, the receiver structure was redesigned with low-complexity and low-power detection devices, which solved extremely high power consumption in IoV, including electric vehicles, a large number of deployed roadside units, 5G base stations, and sensors in smart cities. This structure breaks the traditional receiver I/Q modulation structure, uses simple amplitude/phase detection to replace the superheterodyne receivers with the characteristic of high-frequency to intermediate-frequency, solves the problem of high power consumption from the perspective of hardware. Based on this, three non-linear low-power RF receivers are proposed in this thesis. The corresponding probability density functions are derived according to their physical circuit structures. It laid the research foundation for the subsequent chapters, including the analysis of reachable rate and communication transmission theory. Deploying these low-power receivers in IoV’s communication nodes and 5G base stations, also including the vehicles themself, can fundamentally reduce the entire car networking system’s energy consumption.

(3) Achievable Rate Analysis of High Energy-efficiency Non-linear MIMO for the Internet of Vehicles

In response to challenge 3, because the non-linear RF receiver breaks the traditional RF receiver structure, the received signal is no longer a traditional complex signal, but an amplitude signal or phase signal with losing half dimension of the information. Due to the nonlinearity of the amplitude-obtaining operation or the phase-obtaining operation, the low-consumption receivers' structure does not have
a closed-form solution when calculating their capacity. Therefore, it is necessary to use mutual information theory to calculate its uplink achievable rate from the perspective of information theory. Based on Chapter 2’s conclusion: “Due to the fact of multiple reflection signals in dense urban scenarios, the V2V channel model can be approximated as a Gaussian channel”, then three non-linear MIMO systems can be analyzed and solved under the Gaussian channel. While after this chapter proposed the general calculation framework, an efficient antithesis quasi-Monte Carlo algorithm is proposed, which effectively solves the difficult problem of high-dimensional integration and provides a theoretical foundation in non-linear MIMO theory.

(4) Gaussian mixture model-based EM signal processing algorithm in HPO-MIMO system

In response to Challenge 4, this thesis studies the channel estimation and multi-user detection algorithms for non-linear MIMO systems from the iterative solution’s perspective. Specifically, the problem is solved with Expectation-Maximum (EM) and Gaussian Mixture Model (GMM). Besides, by introducing one traditional RF link into the -phase MIMO system, the least square (LS) method is used to solve the phase ambiguity or amplitude ambiguity problem in the non-linear receiver’s received signal. The simulation results verify the high convergence and effectiveness of the proposed algorithm.

1.4.2 Thesis Organization

This thesis focuses on the theoretical and technical research of non-linear MIMO for urban vehicle-to-vehicle communication. It includes a total of six chapters. Chapter 2, 3, 4, and 5 correspond to the above four research parts, and chapter 6 concludes, and chapter 7 summary the future work. The relationship between each chapter is shown in Figure 1.10.

The thesis is organized as follows.
Chapter 1: Chapter 1 gives an overview of this research. After a brief introduction to this thesis’s research background, the non-linear MIMO technology involved in solving extreme power consumption is defined for this thesis. In the following chapters, the vehicle-to-vehicle communication channel modeling and the related works of non-linear MIMO technology are introduced in detail. The challenges of the current two technologies are summarized, and the necessity of low-power green communication vehicle networking systems is emphasized. Finally, based on the challenge of the green IoV, the main research content and innovation of this thesis are summarized. This chapter also illustrates each chapter’s relationship, and the organization structure of this thesis is given.

Chapter 2: In chapter 2, the V2V channel modeling based on real geographic location information and actual vehicle driving information is studied for the chal-
lenges brought by V2V scenarios. Precisely, when modeling the V2V channel, real geographic location information and environmental information around the communication vehicle pairs are considered to build the small/large-scale fading model. Furthermore, based on the proposed R-tree algorithm to quickly determine the type of link between communication vehicle pairs. This chapter also proposed geometric methods to analyze the multi-hop reflection, diffraction type between vehicle pairs. The simulation results show that the proposed GWV2V channel model, compared with the EVA70 fading channel proposed by 3GPP and the WINNER II channel commonly used in business, has more realistic characteristics for the complex and differentiated driving environment.

Chapter 3: In Chapter 3, aiming at the extremely high power consumption of traditional IoV, the design problem of low power non-linear receiver structure is studied. First, improve the existing low-power receivers and propose three different low-power receivers, named non-linear receivers. Their mathematically modeled and corresponding probability density functions are derived for subsequent chapters’ convenience after describing their specific physical structure. Finally, by analyzing and comparing the power consumption of traditional receivers and non-linear receivers, it is shown that when non-linear receivers are applied to roadside units, 5G base stations, and various communication nodes in the IoV, they can effectively achieve “New infrastructure” requires green communications in future.

Chapter 4: Chapter 4 analyzes the uplink achievable rate of three different non-linear MIMO systems from the perspective of information theory and proposes a general calculation frame. An efficient antithesis quasi-Monte Carlo algorithm is designed to deal with the high complexity problems caused by the excessive number of iterations in numerical analysis. Theoretical analysis and simulation results show that the designed RF structures can reach the traditional RF performance with increased antenna numbers but less overall power consumption. The trade-off between
power consumption and the uplink achievable rate of non-linear MIMO systems also reveals that the non-linear RF structures increase the power efficiency by up to 2.3 times compared to the traditional receiver structure. We also provide an algorithm named Antithetic-QMC based on LDS for dealing with the multidimensional integration problem. Compared with the traditional MC algorithm, our algorithm is more efficient. Moreover, we reveal that when the skew-normal distribution is used as signaling, the non-linear MIMO systems can achieve better performance than the Gaussian distribution.

Chapter 5: This chapter discusses future works. In chapter 5, in view of the challenges brought by the transmission technology of non-linear MIMO receivers in the IoV, the channel estimation and multi-user detection algorithms of non-linear MIMO systems are studied from the perspective of iterative solution. Specifically, because non-linear MIMO system observations lose half the dimension of information, such as amplitude information or phase information, there exists the ambiguity problem of phase or amplitude. In order to solve this ambiguity problem, this chapter transformed the non-linear MIMO channel estimation and multi-user detection problems into non-convex optimization problems, and the Expectation-Maximization Algorithm (EM) algorithm based on Gaussian Mixture Model (GMM) is proposed. The simulation verifies the high convergence and effectiveness of the proposed algorithm.

Chapter 6: This chapter discusses future works.

Chapter 7: This chapter summarizes the research of this thesis and highlights the contributions of this thesis.
Chapter 2

Geometry Enhanced Winner II Channel Model based on real city geographic location information

2.1 Introduction

Chapter 1 has clarified that the traditional cellular channel model is no longer applicable to the Internet of Vehicles communication scenarios [63]. The new car networking channel needs to consider the vehicle’s mobility and the driving environment’s variability [64]. V2V scenarios can be subdivided into the urban environment, suburban environment, highway environment based on different situations such as the buildings, bridges, trees, and parked cars around the road. Due to the complex driving environment in the V2V scenario, the vehicle flow density will also significantly affect signal propagation. Existing research on channel modeling of vehicle networking is divided into two categories: the first category is ray tracing technology [65], that is, the channel model is established by measuring the real driving environment to obtain information; the second category is establishing the channel through statistical information Model [59], that is, according to the probability distribution of different scenes (for example, WINNER II [66]), estimate the statistical characteristics of the channel, to model the large and small scale fading in a specific scenario.

Although the ray tracing technology improves the channel model’s accuracy by utilizing the location, size and height of buildings and trees in the real world, the calculation involved in this method is too cumbersome. In large-scale vehicle networking scenarios, this method will become challenging. The channel modeling
method based on statistical characteristics can effectively solve the problem of high computational complexity in the mentioned ray tracing technology. The statistical channel model can generate the channel model according to the predefined statistical probability distribution in different scenarios. However, the predefined statistical channel model is not always suitable for the actual scenario, and a small parameter change will cause a large deviation between the channel model and the channel in the actual scenario. Therefore, the universality of statistical channel models is not as good as ray tracing modeling methods. The above two methods have their advantages, but the disadvantages are also very prominent.

Thus, traditional cellular channel models are not suitable for vehicle communication scenarios[67]. The development of a channel model that considers the characteristics of vehicle networking is necessary[68]. Current research on vehicle networking channel modeling is generally divided into two categories: ray tracing[69, 70, 71], in which a channel model is established by measuring true information, and statistical channels[72, 73], in which time profiles and fading characteristics are statistically simulated based on specified probability distributions (e.g., Winner II [74]).

Current geometry-based models, such as GEMV$^2$ [75], yield results at a large scale that are in very good agreement with the real world. However, GEMV$^2$ naively models small-scale signal variations by a Gaussian distribution (e.g., zero-mean normal distribution $N(0,\sigma)$) and uses only the received power. In addition, non-line-of-sight (NLOS) links are described only by single-interaction reflections. Due to the newly presented features of the above-described vehicles in real-world scenarios, such as urban areas, the NLOS link of a radio wave can be subject to many reflections rather than a single-interaction reflection.

This chapter aims to build a novel Geometry Enhances Winner II V2V (GWV2V) channel modeling method based on the city’s real geographic location information
that can reflect real-world driving scenarios. It not only uses the real geographic location information to build a large-scale fading model, but also uses the location information of the surrounding environment of the communication vehicle. The small-scale fading model and the Doppler frequency offset are modeled by obtaining the two communication vehicles’ relative movement speed. Due to the comprehensive use of the real geographic location information and vehicle driving information provided by sensors and roadside units in the IoV. This modeling method is more adaptable to complex urban environments than traditional statistical channel models, and it can solve the problem of high computational complexity brought by ray tracing technology at the same time.

The main contributions of this chapter are as follows:

(1) To reflect reality, we use the vehicle locations that are available from traffic mobility by the SUMO model and geographical maps of a specified area (e.g., the Manhattan region in the US) obtained from projects such as OSM. In this manner, the line-of-sight (LOS) and NLOS for each link can be precisely evaluated according to the dimensions of nearby buildings and vehicles.

(2) For the NLOS links, we not only model single-bounce reflections but also present an approach to modeling the multiple bounce reflections of signals from arbitrary buildings and vehicles based on the geometry.

(3) Specifically, R-trees [76] are used to store information about the outlines of vehicles and buildings. With this method, the efficiency of determining the link type can be greatly improved.

(4) Statistical models of small-scale fading effects (e.g., Doppler frequency spread) in WINNER II are improved based on real geographical information.

The remainder of this chapter is organized as follows: Chapter 2.2 describes the general structure of our proposed Geometry Enhanced Winner II V2V Channel.
Model (GWV2V), and two related software programs are introduced. The specific fading details of the GWV2V, including the large-scale/small-scale effects and Doppler frequency spread, are given in Chapter 2.3. Chapter 2.4 first introduces the LTE-V link-level simulation platform based on the 3GPP standard [77] [78] [79], and then verifies and evaluates the performance of the proposed algorithm. Finally, Chapter 2.5 concludes.

2.2 The general structure of the Geometry Enhanced Winner II V2V Channel Model (GWV2V)

The vehicle channel model is characterized by delay spread, multi-path fading and Doppler frequency spread, which are determined by the environment and relative speeds of the vehicles[80]. Compared with classical communication scenarios, as shown in Figure 2.1, vehicle networking has the following new features:

(1) A radio signal from the transmitter can be easily obstructed by buildings and large trees due to the low terminal height of a vehicle.

(2) Since the transmission scenario is highly sophisticated, radio waves will be reflected many times, and abundant signals occur such as in the case of a road surrounded by several tall buildings.

(3) Due to the high speeds of vehicles, Doppler spreading will be considerable.

(4) Changes in the environment render wireless channels unstable and affect the propagation of a signal and channel responses, producing time-variant properties characterizing the channels.

Based on the above-mentioned new features, vehicle speed, antenna height, and complex and changeable wireless channel environment are the main reasons that affect signal fading in V2V communication scenarios. Therefore, the IoV urgently needs a channel model that can effectively describe the diverse characteristics. This
Figure 2.1: The general structure of the proposed channel model in the VCPS: there are two planes in the VCPS, the physical-plane and the cyber-plane. The physical-plane describes the real driving environment as shown in the bottom portion, which is very complex. We can see some communication vehicles are shielded by buildings, some are obstructed by vehicles, and some are shielded by large trees. The upper portion shows how our proposed model works in the cyber-plane.
section first introduces the GWV2V channel model and then introduces how to use the R-tree structure to accelerate the judgment of the link type between communication vehicles.

In order to ensure that the channel model generated by GWV2V can accurately reflect the real urban vehicle driving environment, firstly, OpenStreetMap (OSM) [81] software is used to replace roadside units and communication nodes to obtain real-world geographic location information. Secondly, use the Urban Traffic Simulation (SUMO) [82] system to obtain the environmental information of the driving vehicle (step 1 in Figure 2.2). Regarding the entire vehicle driving link as a continuous process, SUMO can record vehicle driving information in real-time. This behavior is similar to installing a high-precision global positioning system (GPS) on each vehicle. Moreover, combine the city map information obtained by OSM and the driving information obtained by SUMO to draw the vehicle’s current environment model. According to the above two public software technical supports, specific vehicles’ driving characteristics in different scenarios can be extracted, so improving the reliability and accuracy of the modeling channel can be achieved.

After obtaining the driving environment model, the link type between every communication pair should be judged in step 2 of Figure 2.2. We classify the link type as LOS, NLOS-B or NLOS-V. To judge the link type efficiently, the R-tree [76] structure is adopted. As shown in Figure 2.3, we converted the map of BUPT into an R-tree structure, in which every blue box represents a building. When a vehicle is moving (Figure 2.3 (left)), we determine whether a block of the location exists between the two vehicles (including the building and vehicle with a blue box) according to Figure 2.3 (right). If a block exists, the two vehicles are considered to have an NLOS link. If a block does not exist, they have an LOS link. An NLOS link can be distinguished by being an NLOS path caused by vehicles, which is referred to as NLOS-V, or an NLOS path caused by buildings, which is referred to as NLOS-B.
Figure 2.2: The general structure of the GWV2V channel model. A total of 3 steps are shown for calculating the channel response of the real city. Step 1 shows the process of loading the vehicle and map information. Step 2 shows the process of judging the link type using the R-tree structure. Step 3 shows the process of calculating the fading effects.
Since storing data according to this method greatly increases the search speed, we are able to achieve high efficiency when the channel model is generated for a large city.

![R-tree structure](image)

**Figure 2.3 : R-tree structure**

When the links of all communicating vehicle pairs are clearly classified, the reflection and diffraction phenomena of each NLOS link should be calculated. We consider 1-3 bounce reflections because the phenomenon of multiple-bounce reflections of signals from buildings and vehicles is always present in reality. We do not consider reflections with more than 4 bounces because the received power would be too low to facilitate communications among vehicles. Signal fading effects and multi-path time delays are generated after exploiting the outlines of vehicles and buildings to determine the LOS/NLOS link type and calculate the multiple-interaction reflections and diffractions in step 3 of Figure 2.2. The specific details will be expanded in section 2.3.

The GWV2V model simulates large-scale and small-scale fading effects based on the real map information of the modeling region (e.g., the placement of buildings). Signal fading effects and multi-path time delays are generated after exploiting the LOS of vehicles and buildings to determine the LOS/NLOS link type and calculate the multiple-interaction reflections and diffractions. The fading of a multi-path
signal is calculated in a geometric manner, and channel responses that reflect the signal variation are generated. Using this approach, GWV2V has the following advantages:

(1) GWV2V not only fully reflects the impact of different scenarios on V2V communications but also reveals the impact of different geographical locations, thus overcoming the disadvantages of the poor universality of a statistical channel.

(2) GWV2V uses common map information without the complex geographic information database of the ray-tracing model. Consequently, the cost of modeling for a particular area is reduced.

(3) The computations of multi-path fading are based on geometry, have low computational complexity and can be employed for massive V2V communication simulations.

The disadvantage is that even though 5.9 GHz is still in a clean frequency band (5.9GHz is a special-use frequency band for LTE-V), there is no interference from the electronic signals of other communication devices. However, in the near future, perhaps this band will be assigned other signals, we still need to continue to study the impact of channels from other electronic devices.

### 2.3 Fading effect of the GWV2V Channel Model

As shown in formula (2.1), the channel response consists of large-scale fading and small-scale fading (including Doppler frequency offset). The detailed modeling
process is given in subsections 2.3.1, 2.3.2 and 2.3.3.

\[ H_{u,s,n}(t) = \sqrt{P_n} \sum_{m=1}^{M} \begin{bmatrix} 1 \\ F_{rx,u,V} (\phi_{n,m}) \end{bmatrix}^T \exp \left(j\Phi_{n,m}^{uv}\right) \sqrt{\kappa^{-1}} \exp \left(j\Phi_{n,m}^{vh}\right) \]

\[ \begin{bmatrix} F_{tx,s,V} (\varphi_{n,m}) \\ e^{j2\pi\lambda_0^{-1}\sin(\varphi_{n,m})} \\ e^{j2\pi\lambda_0^{-1}\sin(\phi_{n,m})} \\ e^{j2\pi n, m} \end{bmatrix} \]

\[ e^{jd_s 2\pi\lambda_0^{-1}\sin(\varphi_{n,m})} e^{jd_u 2\pi\lambda_0^{-1}\sin(\phi_{n,m})} e^{j2\pi n, m} \]

(2.1)

where \( P_n \) is the received power representing the large-scale fading. The multi-path parameters, including the azimuth arrival angles (AOA) \( \varphi \) and the azimuth departure angles (AOD) \( \phi \), represent the small-scale fading. \( F_{rx,u,V} \) and \( F_{rx,u,H} \) are the antenna element \( u \) field patterns for vertical and horizontal polarization, respectively, and \( d_s \) and \( d_u \) are the uniform distances (m) between the transmitter vehicle and the receiver vehicle.

### 2.3.1 Large-scale fading of the channel model

For the three different links illustrated in the previous section, different models are used to compute the large-scale fading. For LOS links, since the transmitting and receiving antennas of the vehicles on LOS links are short and close to the ground, the corresponding model is a two-ray ground reflection model. Since the side of a vehicle is edged with the signal for an NLOS-V link, a knife-edge diffraction model is adopted. For NLOS-B links, since buildings cause signal reflection and diffraction, these two models are calculated.

The received power \( P_n \), which represents the large-scale fading in formula (2.1), is extended to formula (2.2).
\[ P_n = \frac{|E_{TOT}|^2 \lambda^2}{480\pi^2}, \]  

(2.2)

where \( \lambda \) is the wavelength and \( E_{TOT} \) is the resultant \( E \)-field envelope, which can be extended to

\[
|E_{TOT}| = \left( \frac{E_0 d_0}{d_{LOS}} \cos(\omega_c(t - \frac{d_{LOS}}{c})) \right) \\
+ \sum_j R_j \frac{E_0 d_0}{d_j} \cos(\omega_c(t - \frac{d_j}{c})) \\
+ \sum_k D_k \frac{E_0 d_0}{d_k} \cos(\omega_c(t - \frac{d_k}{c}))
\]  

(2.3)

\[
D_k = \begin{cases} 
6.9 + 20\log_{10} \left[ \sqrt{(v - 0.1)^2 + 1 + v - 0.1} \right]; & v > -0.7 \\
0; & \text{otherwise}.
\end{cases}
\]  

(2.4)

In formula (2.3), \( \omega_c \) is the angular frequency \( (\omega_c=2\pi f) \), \( t \) is the time at which the \( E \)-field is evaluated, \( d_x \) represents the distance traversed by ray \( x \), \( R_j \) is the reflection coefficient of the \( j \)-th path, and \( D_k \) in formula (2.4) is the diffraction coefficient of the \( k \)-th path.

For the LOS link, the first two parts of formula (2.3) are represented by the two-ray ground reflection model. For the NLOS-V link, the knife-edge diffraction model is illustrated in the last part of formula (2.3). For the NLOS-B link, formula (2.3) is applied. Finally, the received power \( P_n \) in formula (2.2) can be obtained.

### 2.3.2 Small-scale fading of the channel model

To model small-scale fading, we employ the WINNER II model as a reference. However, when calculating the specific parameters, we do not employ the statistical data of WINNER II and instead calculate the previous parameters according
Figure 2.4: Calculated multi-path based on geometry method

to the information on the target vehicles and their surrounding environment. In a real wireless channel, a radio signal is always reflected and diffracted many times. Clustered phenomena exist in the temporal and spatial dimensions. For the time propagation characteristics of multi-path signals in the same cluster, all sub-paths within the cluster have the same time delay. For the spatial propagation characteristics of multi-path signals in the same cluster, two parameters - the central AOD direction of the angle of arrival (mean) and the angle spread (shifting) - are used to describe the direction of the arrival of the radio wave. Here, multiple paths are calculated based on the geometry. The reflection, diffraction and scattering of signals are considered, as shown in Figure 2.3. Two-bounce reflection paths are calculated
based on the geometry in Figure 2.4 (a) (b), and the diffraction paths are calculated based on the geometric methods in Figure 2.4 (c).

In Figure 2.3 (a), (b), the two-bounce reflection paths are calculated as follows:

1. Calculate the mirror points of each Tx and Rx link.
2. Connect the Tx and Rx mirror points as the line segment $L$.
3. The R-tree is used to determine whether there is an intersection point between each of the two building edges and the line segment $L$ in the communication ellipse. If an intersection point exists, then the two points are the reflection points, which are denoted as $S_1, S_2$.
4. Calculate the distances, AOA $\varphi$ and AOD $\phi$ of $\text{Tx-S}_1\text{-S}_2\text{-Rx}$ as a cluster of $\text{Tx-Rx}$ links.
5. Each cluster is fixed with 20 sub-paths. The delay, AOD $\phi$, AOA $\varphi$ and power of each sub-path are calculated.

2.3.3 The Doppler frequency spread

In a V2V communication scenario, there is relative motion between the receiver vehicle and the transmitter vehicle. The result of this relative motion is that the carrier signal obtained by the receiver vehicle will undergo a Doppler shift; this phenomenon is referred to as the Doppler effect. Consequently, the operating frequency $f$ of the communication system is not accurate due to the influence of multiple Doppler effects. Therefore, calculating a real-time, accurate model of the Doppler effect is very important for efficient vehicle communication systems.

A real mobile channel communication environment has many different components, which are determined by reflection, diffraction and scattering. Describing all multi-path components is difficult and complex. To achieve a balance between complexity and efficiency, we have combined the statistical model of WINNER II
and real geographic data to propose a calculation method for the Doppler effect.

Formula (2.5), as a part of formula (2.1), which was illustrated in Section 2.3, describes the Doppler effect:

$$e^{j d_u 2 \pi \lambda_0^{-1} \sin(\phi_{n,m})} e^{j d_s 2 \pi \lambda_0^{-1} \sin(\phi_{n,m})} e^{j 2 \pi v_{n,m} t}.$$  \hspace{1cm} (2.5)

To address the V2V scenario, we fix the above parameters. In formula (2.5), $d_u$ and $d_s$ are the uniform distances (m) between the transmitter vehicle and the receiver vehicle, respectively, and $\lambda_0$ is the wavelength of the carrier signal. The Doppler frequency component $V_{n,m}$ is calculated from the angle of arrival (sidelink), vehicle speeds $v_r$ and $v_t$, and directions of travel $\theta_{v_r}$ and $\theta_{v_t}$ in formula (2.6):

$$V_{n,m} = \frac{\| v_t - v_r \| \cos(\varphi_{n,m} - \| \theta_{v_t} - \theta_{v_r} \|)}{\lambda_0}.$$  \hspace{1cm} (2.6)

Then, the channel model of a specific area is established by calculating formula (2.1) to (2.6). In GWV2V, we calculate the reflection path for three bounces, the diffraction path of one bounce and the random scattering path. Based on the map information, a geometry-based approach is employed. The channel response, which reflects the propagation conditions of the specific communication area, can be obtained by calculating the large/small-scale fading parameters.

2.4 Simulation and Results

2.4.1 Framework of the LTE-V simulator

The LTE-V link-level simulator and its general structure are described in this section. The proposed LTE-V simulator is fully realized in MATLAB according to the 3GPP Release 14 36.211[83], 36.212[84], and 36.213[85] standards. The general structure of our V2V simulator is depicted in Figure 2.5. The output baseband signal
from the transmitter (Tx) enters the channel model part. Subsequently, the signal is processed in the receiver (Rx). Before the simulation starts, all necessary settings are reported to the simulator. The signalling information also includes the Sidelink (the link between the UE and the UE defined in [83]) Control Information (SCI). The performance of the LTE-V simulator includes the Block Error Rate (BLER).

Figure 2.5: General structure of LTE-V simulator

In contrast to the uplink and downlink, communication over the sidelink uses communication periods that are periodic in the time domain. Each sidelink period includes instances of the Physical Sidelink Control Channel (PSCCH) and the Physical Sidelink Shared Channel (PSSCH), which carries control information and data. 3GPP defines procedures related to transmission and reception on the PSCCH and PSSCH. Instead of using PSCCH resources that are assigned by an eNB, terminals with data to send select random resources from the PSCCH resource pool to send a control message that tells potential receivers, all of which monitor the PSCCH, where and how the transmitting UE’s pending data will be transmitted in
the PSSCH. Upon successful reception of a control message, a UE can tune to the indicated Physical Resource Blocks (PRBs) in the PSSCH. Any terminals that fail to receive and decode the PSCCH message will not be able to receive the advertised data transmission in the PSSCH. In our simulator, all the SCI of PSCCH in a given period can be transmitted at most twice, and the data of PSSCH can be transmitted at most 4 times. The communication pairs randomly select PRBs from the PSCCH resource pool to transmit the SCI. The SCI contains all information on the data (such as the number of PRBs used for data transmission and the start position of the PRB). After receiving and decoding the SCI, the receiver can obtain the data from the PSSCH resource pool.

Our LTE-V transmitter model with the signal processing chain is depicted in Figure 2.6. The transmitter contains two parts. The first process, which is referred to as the PSSCH, involves a CRC attachment, sub-block segmentation, channel coding and rate matching. The second process, which is referred to as the PSCCH, involves scrambling, a modulation mapper, a layer mapper, a transform pre-coder, pre-coding, a resource element mapper, and SC-FDMA signal generation.

The original data bits are randomly generated. Then, the bits are scrambled and forwarded to a coder parser. The data are coded using turbo channel coding. Each stream is interleaved, and constellation mapping is performed (QPSK in PSCCH and QPSK and 16 QAM in PSSCH, as defined in [83]). Next, an SC-FDMA symbol is formatted by mapping data symbols and a pilot signal according to a defined system bandwidth. Transmission mode and an Inverse Fast-Fourier Transform (IFFT) are performed. To avoid Inter Symbol Interference (ISI), a Cyclic Prefix (CP) is inserted as a guard time for the SC-FDMA time signal and is transmitted over transmit antennas for all types of channels.

The structure of the receiver model is the inverse of the transmitter; the details
Figure 2.6: Transmitter model of LTE-V simulator.

Figure 2.7: Receiver model of LTE-V simulator.
are shown in Figure 2.7. In the LTE-V receiver, the FFT transforms the received signals from the time domain to the frequency domain, which is coherently demodulated. Following resource element de-mapping, the LS method is employed as the channel estimation at the receiver according to the Demodulation Reference Signal (DMRS). In the LTE-V sidelink, two DMRS symbols are employed. After channel equalization, QAM demodulation transforms the equalized QAM symbols as soft bits. Data bits are recovered after the processes of descrambling, de-mapping, and turbo decoding.

### 2.4.2 EVA-Fading70 and WINNER II V2V channel models

In this subsection, the performance of the LTE-V is analysed according to the BLER. The 3GPP Extended Vehicular A model (EVA) channel model and the WINNER II V2V channel model are employed as references. In the 3GPP TS 36.104/36.141 standards, the channel models are divided into three types: the Extended Pedestrian A model (EPA), the Extended Vehicular A model (EVA), and the Extended Typical Urban model (ETU). We apply the EVA channel model as the reference model. The channel parameters are listed in 36.104/36.141 Appendix B2.

The WINNER II channel [74] is a relatively popular channel in the current academic circles. We have upgraded the WINNER II channel according to the vehicle protocol of 3GPP TS 36.885 to create a type of channel with vehicle communication features and named it the WINNER II V2V channel model. Although this channel is a relatively mature channel, it has the following disadvantages:

1. The LOS and NLOS from the vehicle communication link should be present according to the pre-modelled channel. However, the method for determining the pre-modelled channel does not correspond to real-world situations.

2. The computation of large-scale fading adopts the simple Manhattan model
(nine boxes in the 3GPP, not the real city of Manhattan), which rarely considers the influence of the distance between the transmitter and receiver or the influence of the real environment on signal variations.

(3) The computational parameters of small-scale fading are statistical parameters, which do not reflect the influence of the real environment on signal variations.

(4) The speed of the vehicles can only be set to a fixed value, but in reality, the speed constantly changes with the demand. Therefore, the Doppler spread cannot be calculated precisely.

2.4.3 Simulation Parameters

To compare the simulation results, we use the same initial simulated parameters for the 3 channel models. According to the requirements of the VANET standards, the transmission bandwidth is set to 20 MHz. The noise in the different channel models represents Additive Gaussian White Noise (AWGN). The QPSK modulation method is utilized in three different channel models. The length of the packet is set to 872 bits. In this paper, SNR-BLER was chosen as an indicator of the performance of the response channel. The Signal-to-Noise Ratio (SNR) represents the strength of the noise in the channel. Higher SNR (dB) indicates poorer channel conditions. The BLER is the block error rate, which reflects the percentage of transmission error blocks in all transmitted blocks. In general, the better the channel quality, the lower the block transmission error rate and the higher the BLER. The results are the averages of 2000 simulation runs. Note that the vehicle’s speed is fixed at 20 m/s in the WINNER V2V channel model, but in our proposed model, the vehicle’s speed changes randomly from 0 m/s to 20 m/s.
Figure 2.8: The performance of BLER in three different channel models including the GWV2V channel model, EVA channel model and the LOS/NLOS link in the WINNER II V2V channel model.
2.4.4 Performance Evaluation

Figure 2.8 shows the SNR-BLER curve for the three channels. The x-coordinate denotes the SNR (dB), and the y-coordinate represents the BLER. Figure 2.8 provides three observations. First, the general trend of the three models indicates that the BLER gradually decreases to 0 dB as the SNR increases. Second, compared with the EVA channel and the BLER of the WINNER II V2V channel, the simulation results of GWV2V are different. The GWV2V model uses the real location of vehicles and the outline of the surrounding buildings and trees. When using this model, the obtained data are based on the distribution of the vehicles in the designated map. Each communication pair is the LOS link or NLOS link; specifically, the BLER performance of the channel based on statistical information differs from the BLER performance of the geometry-based channel. In the WINNER II V2V channel, the performance of the LOS link exceeds the performance of the NLOS link.

The EVA channel is a fading channel that is regulated by 3GPP. This channel has a general statistical feature - the Doppler shift is customized - that does not change with time. Therefore, the EVA channel is applied to certain Doppler shift scenarios. The WINNER II V2V channel is divided into the LOS scene and the NLOS scene because this channel model must preset the simulation for the LOS link or the NLOS link. In the case of a scene with multiple vehicles, defining the LOS and NLOS probability distributions is difficult. Therefore, the WINNER II V2V channel model is suitable for the simulation of known LOS or NLOS links of vehicles. The GWV2V channel model is suitable for complex urban blocks, and accurate channel information can be obtained if specific location information about buildings in the known area and its contour size can be obtained.

It can be seen from the above three channel characteristics that the proposed
GWV2V adopts geographic location information from the real environment, which makes our channel model more geographically sensitive than the statistical model (e.g., 3GPP-EVA and WINNER II V2V). The statistical model cannot be adapted to local conditions due to the use of a uniform distribution. However, our proposed channel model can calculate the corresponding channel response according to the changes in different geographical environments. Therefore, our proposed model is more realistic than the traditional model.

Figure 2.9: Three different regions of Manhattan, including the City Park area (red box area), Street area (blue box area) and the overall Manhattan area (black box area).

In order to describe the performance of the proposed GWV2V channel in detail, this chapter carries out channel modeling for different areas of Manhattan, USA (Fig. 2.9) and different areas around the Forbidden City in Beijing (Fig. 2.10). Fig. 2.9 shows that the red box represents the Manhattan urban garden area, which
Figure 2.10: Three different regions of Beijing University of Post and Telecommunication campus including main building area, the south gate area and the whole region of BUPT. The main building area without shelter, made up of squares and avenues.
is characterized by relatively open space (consisting of squares with almost no tall buildings around). When vehicles drive in this area, most of them are LOS. The blue box area represents the Upper East Side of Manhattan, characterized by many high-rise buildings and denser buildings. When a vehicle is driving in this area, the probability of generating an NLOS is high. It can also be observed from the map, the entire Manhattan area (black box) is characterized by many tall buildings, which are extremely easy to cause occlusion, and the probability of vehicles traveling randomly in the entire Manhattan area as an NLOS is higher.

Similarly, in Fig. 2.10, the red box is the Zhongnanhai area. Due to its particular geographical location (only two roads exist on the left and right sides of the Zhongnanhai left area), most of the vehicles driving in this area are LOS. The blue box area is the Wangfujing area, which is characterized by a large number of shopping malls, high-rise buildings, and residential buildings. The road environment is complex, causing most vehicles formed in this area to be NLOS. The black area is the Forbidden City area, including the Zhongnanhai area, the Forbidden City area, and the Wangfujing area. Its characteristic is that most communication vehicles are LOS due to the simple road environment when vehicles are driving in the Zhongnanhai area and the Forbidden City area. Although the Wangfujing area is densely built, when vehicles are randomly traveling in the entire Forbidden City area, the probability that vehicles are randomly distributed throughout the Forbidden City area are LOS links.

Figure 2.11, Fig. 2.12 show the effects of different regional channels of Manhattan on the performance of BLER in GWV2V, respectively. In Figure 2.11, corresponding to the different areas of Manhattan in Figure 2.9, it can be observed that vehicles are driving in the city park area. Since the city park is relatively empty, the probability that the link between vehicles is LOS is higher. Therefore, the channel quality is the best, and the corresponding SNR-BLER performance is the best. Under
Figure 2.11: The BLER performance of GWV2V in different areas of Manhattan, including the whole Manhattan region, the City Park area and the Street area of Manhattan.
Figure 2.12: The BLER performance of GWV2V in different areas of Beijing University of Post and Telecommunication including whole region of BUPT, main building region of BUPT and the south gate of BUPT
the same lever of SNR, the block error rate within the city park is the lowest. When vehicles are randomly traveling within the upper east area of Manhattan, the probability of NLOS between vehicles is higher, so the channel quality is slightly lower, and the corresponding SNR-BLER performance is in the middle. When vehicles are randomly traveling in the entire Manhattan area, the probability of NLOS transmission between vehicles is higher. Therefore, compared with the other two areas mentioned above, the channel quality in the Manhattan business district is the worst, and the corresponding SNR-BLER showed the worst performance.

Similarly, in Figure 2.12, when a vehicle is driving in the Zhongnanhai area shown in Figure 2.10, the link between vehicles has a higher probability of being LOS. This is because there only exist two major roads in the Zhongnanhai area. When vehicles are driving in the Wangfujing area, the complicated environment causes the paths between communication vehicles to be NLOS. Their performance is reflected in Figure 2.12. That is, the SNR-BLER performance is the worst, which can reflect the weaker channel quality. When vehicles travel in the entire Forbidden City area (corresponding to the black triangle curve), their corresponding SNR-BLER performance is close to the Zhongnanhai area (corresponding to the red square curve) and better than the Wangfujing area (corresponding to the blue dot curve). This observation is slightly different from the SNR-BLER curve in different areas of Manhattan in Figure 2.11. In Figure 2.11, the block error rate performance of the entire Manhattan area is the worst, but in Figure 2.12, the entire Forbidden City area has the worst performance, but the block error rate performance is in the middle. This is because the two maps contain different areas’ size, and each area base contains a complex urban area, which results in different performance. This also reflects from the side that the proposed GWV2V channel can better reflect different SNR-BLER performance in different driving environments, and contributes to improving the accuracy of physical layer data.
2.5 Chapter Conclusion

This chapter proposes a realistic LTE V2V channel propagation model named Geometry Enhanced Winner II V2V (GWV2V) Channel Model and presents the LTE V2V link-level simulator. First, the existing vehicle channel models and their advantages and disadvantages were analyzed. The vehicle channel model, based on a geometric model combined with a stochastic model, was the best model form. Second, to produce a closer realistic propagation model in GWV2V, the outlines of the buildings and trees of the surrounding environment and vehicles’ movements were combined. Therefore, the NLOS/LOS link type could be precisely calculated. In the NLOS link, we considered not only a single interaction but also the multiple-interaction reflections and diffractions. After the link type is judged, the large-scale fading model can be calculated according to different types. In calculating the small-scale fading model and Doppler frequency offset, the communication vehicle’s driving environment information is fully considered so that the proposed GWV2V channel and the real driving environment information are more matched. Finally, this chapter conducts simulation tests under three different channel models based on the LTE-V link-level simulation platform, including the GWV2V channel model proposed in this chapter, the EVA70 fading channel model of 3GPP, and the WIN-NER II channel model with the characteristics of V2V. The results show that the GWV2V channel model proposed in this chapter has characteristics more in line with urban driving characteristics.
Chapter 3

Structure Design of Power-efficiency Non-linear Receiver for Internet of Vehicles

3.1 Introduction

In the green vehicle networking ecosystem, roadside units, 5G base stations, and infrastructure face many deployment requirements [86]. In an environment with a large number of communication units, the roadside units are required to have low energy consumption, and those communication sensor devices that can only be powered by batteries in an urban environment are required to have low energy consumption. Besides, in the 5G times, the power consumption caused by the massive deployment of 5G base stations has become a hot topic. Moreover, with the electric vehicle industry’s development, electric vehicles will also consider energy consumption factors.

This chapter will introduce non-linear MIMO [87] technology to solve this problem effectively. The non-linear MIMO system combines the energy-saving design characteristics of non-linear devices and MIMO systems’ high-performance gain. Its receiver uses non-linear devices with low cost and low power consumption, including envelope detector (amplitude detector), phase detector, etc. Only obtain the amplitude or phase observation from the received radio frequency complex signal for baseband signal processing. Due to low-cost, low-power non-linear devices, the design of the non-linear MIMO system receiver will be simpler than traditional MIMO systems, and power consumption and manufacturing costs will be greatly reduced.

The non-linear MIMO system combines non-linear technology with multi-antenna
technology, thus fusing the advantages of the two technologies: (1) Ultra-low power consumption characteristics brought by non-linear modulation and detection; (2) Use the spatial multiplexing brought by multiple antennas to obtain the higher rate.

Those types of receivers have low power consumption characteristics because even if multiple non-linear RF links are used, the total power consumption is still lower than the power budget of a single traditional RF link. Besides, the cost of non-linear RF devices is extremely low, and even if they are used in large quantities, their cost is much lower than that of traditional RF links containing high-precision ADCs. The detailed analysis will be carried out in this chapter. In summary, in the future urban car networking environment that requires massive wireless communication nodes and large-scale deployment of 5G “new infrastructure”, low-power non-linear MIMO systems may become a key technology.

The contributions of the chapter can be summarized as follows.

(1) In order to build a green vehicle networking ecosystem, this chapter will re-design the receiver structure through low-complexity, low-power RF devices. Those receivers are applied to electric vehicles, roadside units, 5G base stations, and sensors deployed in large numbers. Therefore it can fundamentally solve the problem of excessive power consumption in the Internet of Vehicles.

(2) Based on two nonlinear low-power RF receiver structures, a -phase receiver and an improved version of the phase-only receiver are proposed: phase-only+1bitADC receiver.

(3) According to their physical characteristics, this chapter deduced the corresponding probability density function, the theoretical analysis and communication transmission bedding foundation for the further study of the achievable rates after given those receivers’ hardware structures.
(4) The power consumption analysis of the traditional receiver and the RF link of the nonlinear receiver provides a sufficient basis for the deployment of the nonlinear receiver in a large number of vehicle networking communication nodes.

The rest of this chapter is organized as follows.

Section 3.2 first gives the mathematical model of the nonlinear RF receiver, then gives the probability density functions of three different nonlinear receivers, and finally leads to the non-linear MIMO system model. Section 3.3 introduces the three non-linear RF receiver hardware structures used in this paper. Section 3.4 analyzes traditional RF receivers’ power consumption and nonlinear RF receivers and gives three application scenarios in the IoV. Section 3.5 concludes this chapter.

### 3.2 Hardware structure of Non-linear RF Receiver

In order to decrease the total consumed power of the RF chain, the paper first analyzes the conventional RF chain’s circuit power consumption, and then redesign the RF chain structure at the receiver side. The structure of the conventional RF chain can be seen as Fig.3.1(a), and it consists of the band-selection filter, low-noise-amplifiers (LNAs), voltage-controlled oscillators (VCOs), RF synchronization, quadrature VCO (QVCO), phase-locked loop (PLL), programmable gain amplifiers (PGAs), distinct type filers and high-resolution analog-to-digital converters (ADCs)[?]. As seen from the right side of Fig.3.1(a), the conventional RF chain processes complex data separately from the real and imaginary parts of the signal, therefore two high-resolution ADCs are required.

Distinct from the conventional RF chain, our proposed three non-linear structures down-convert RF signals as their baseband correspondences by inphase-quadrature (IQ)-structured demodulation circuits. In other words, the new non-linear RF structures delete the complex process from high frequency to mediate frequency then to
Figure 3.1: Traditional RF chain structure as shown in (a). Three types of non-linear RF chain structures as shown in (b), (c) and (d). Otherwise, (c1) shows an upgraded version of phase-detector as shown in (c), namely phase-detector with 1 bit-ADC. It replaces the high-resolution ADC in (c) with 1-bit ADC which has smaller power consumption.

baseband in traditional RF chains. Instead, non-linear RF structures directly replace the above complex parts with simple phase detectors or amplitude detectors or half-phase detectors (as shown by the dotted box).

Here, we propose three types of non-linear RF structures. As can be seen from Fig.3.1(b), Amplitude detector and only one high resolution ADC are used to replace the dotted box part in conventional RF chain. Since the amplitude information of the complex signal is acquired, we name the MIMO system with this structure Magnitude Only (MO)-MIMO. Similarly, the MIMO that obtains the phase infor-
mation of the complex signal is named Phase Only (PO)-MIMO. Besides, there is a type of detector which is commonly used in the industry[88], and can only obtain the $\pi$ phase of the complex signal. Such this structure is called Half Phase Only (HPO)-MIMO system. Moreover, in order to seek lower power consumption, (c1) of Fig.3.1) demonstrated an upgraded version of PO-MIMO as demonstrated in (c), namely phase detector with one bit-ADC system. It replaces the high-resolution ADC in (c) with 1-bit ADC[89] (as demonstrating in black dashed outline in right side of Fig.3.1).

### 3.3 System Model

#### 3.3.1 Non-linear MIMO System Model

A single-cell non-linear MIMO system with $N_T$ single-antenna terminals and a BS with $N_R$ antennas in Fig. 3.2 is considered[?], where each antenna is equipped with a non-linear detector (containing $2\pi$-phase detector or amplitude detector or $\pi$-phase detector, and combines with only one high resolution ADC) at the BS side.

![Figure 3.2 : Generic non-linear MIMO system model.](image)

The signal received at BS after obtaining non-linear operator $g(\cdot)$ is formulated
as
\[ y_{Non-linear} = g(r) = g(z + w) = g(Hs + w), \] (3.1)

where \( s \sim \mathcal{CN}(0, \sigma_s^2 I_{N_T}) \) is the transmitting signals by each user. It obeys the complex Gaussian distribution with 0 mean and \( \sigma_s^2 \) variance. \( I_{N_T} \) represents the identity matrix with \( N_T \) dimension. In our simulation, we fix \( E|s|^2 = 1 \).

\( w \sim \mathcal{CN}(0, \sigma_w^2 I_{N_R}) \) is the \( N_R \times 1 \) additive white Gaussian noise vector with 0 mean and \( \sigma_w^2 \) variance. \( H \) represents the \( N_R \times N_T \) channel matrix which remains constant for coherence period. Therefore, \( r \sim \mathcal{CN}(0, \sigma_s^2 HH^H + \sigma_w^2 I_{N_R}) \). The function \( g(\cdot) \) means the non-linear operator of obtaining the received signal \( y \), including the following three different forms of non-linear detectors.

### 3.3.2 Magnitude Only (MO-) MIMO System Model

\[ y_{i,MO} = g_{MO}(r_i) = |r_i| = \sqrt{R\{r_i\}^2 + S\{r_i\}^2} \in \mathbb{R}_+ \] (3.2)

The MO-MIMO \( y_{i,MO} = |r_i| \) is Rician distributed as follows:

\[ f_{MO}(y_i|z_i) = \frac{2y_i}{\sigma_w^2} e^{-\frac{y_i^2 + |z_i|^2}{\sigma_w^2}} I_0\left(\frac{2y_i|z_i|}{\sigma_w^2}\right), \] (3.3)

where \( I_0(\cdot) \) is the zero-th order modified Bessel function of the first kind, can be extended to

\[ I_0(x) = J_0(ix) = \sum_{m=0}^{\infty} \frac{1}{m!\Gamma(m + 1)} \left(\frac{x}{2}\right)^{2m}, \] (3.4)

where \( \Gamma(z) \) is the gamma function, a shifted generation of the factorial function to non-integer values. At high SNR, we use the following approximation for equation (3.3) in these cases:

\[ f_{MO}(y_i|z_i) \approx \sqrt{\frac{y_i}{\pi|z_i|\sigma_w^2}} e^{-\frac{(y_i - |z_i|)^2}{\sigma_w^2}} \left(1 - \frac{\sigma_w^2}{16y_i|z_i|^2} + \ldots\right), \] (3.5)

which is computed using a high argument approximation of \( I_0(x) \). The joint probability density function of MO-MIMO is shown in Fig.3.3.
3.3.3 Phase Only (PO-) MIMO System Model

\[ y_{i,PO} = g_{PO}(r_i) = \angle(r_i) = \text{atan2}(r_i) \in (-\pi, \pi] \]  
(3.6)

The distribution of PO-MIMO $y_{i,PO} = \angle(r_i)$ as follows:

\[ f_{PO}(y_i|z_i) = \frac{e^{-\rho_i}}{2\pi} + \sqrt{\frac{\rho_i}{4\pi}} e^{-\rho_i \sin^2 \phi_i \cos \phi_i} \cdot \text{erfc}(-\sqrt{\rho_i} \cdot \cos \phi_i), \]  
(3.7)

where $\rho_i = |z_i|^2/\sigma_w^2$ and $[\phi_i = (y_i - \angle(z_i)) \text{mod} 2\pi] \in (-\pi, \pi]$. \text{erfc}(x) = $\frac{2}{\sqrt{\pi}} \int_x^\infty e^{-t^2} dt$ is the complementary error function. The joint probability density function of PO-MIMO is shown in Fig.3.4.

3.3.4 Half Phase Only (HPO-) MIMO System Model

\[ y_{i,HPO} = g_{HPO}(r_i) = \angle_\pi(r_i) \]  
(3.8)

\[ = \text{atan} (r_i) \in (-\pi/2, \pi/2], \]

where \text{atan}(\cdot) is the inverse tangent function. In the following content, $\angle_\pi(\cdot)$ is used to replace the function \text{atan}(\cdot).
Theorem 1. The distribution of $\pi$-phase MIMO $y_{i,HPO} = \angle(r_i)$ is as follows

$$f_{HPO}(y_i|z_i) = \begin{cases} 
  f_{PO}(y_i|z_i) + f_{PO}(y_i-\pi|z_i) & y_i \in \left[0, \frac{\pi}{2}\right) \\
  f_{PO}(y_i|z_i) + f_{PO}(y_i+\pi|z_i) & y_i \in \left[-\frac{\pi}{2}, 0\right) 
\end{cases} \quad (3.9)$$

Proof. The PDF of 2$\pi$-phase MIMO $f(y_i|z_i)$ has the form of (3.7). After transforming angle, one can easily obtain the result of Theorem 1.

The joint probability density function of HPO-MIMO is shown in Fig.3.5.
3.3.5 Phase Only (PO-) MIMO with 1bit ADC System Model

\[ y_{i,PO+1bitADC} = Q(g_{PO}(r_i)) = Q(\angle(r_i)) \]
\[ = Q(\text{atan2}(r_i)) \in (-\pi, \pi] \]  

**Theorem 2.** The distribution of PO-MIMO with 1bit ADC is given by

\[ f_{PO+1bitADC}(y_i | z_i) = \int_{Q^{-1}(y_i)}^{+\infty} r_iCN(r_i e^{j\theta}; z_i; \sigma^2) dr_i d\theta_i \]  

**Proof.** It is denoted \( y_i \) as \( |r_i|e^{j\theta} \) under the polar coordinate system. After the phase quantization, \( y = Q(\theta) = Q(\angle(2\pi(r_i))) \), where \( Q(\cdot) \) stand for the phase quantization, it is existed

\[ p(r, \theta | z) = 1_{r \geq 0, 1_{\theta \in [-\pi, \pi]}} r_iCN(r_i e^{j\theta}; z; \sigma^2). \]  

Therefore, the posterior probability density function of \( \theta \) with respect to \( z \) is

\[ p(\theta | z) = \int_0^{+\infty} r_iCN(r_i e^{j\theta}; z; \sigma^2) dr_i. \]  

According to the basic principle of phase quantization, if the quantized phase observation is \( y \), the original non-quantized \( \theta \) is located in area \( Q^{-1}(y) \), where \( Q^{-1}(y) \) stand for the dequantizer. Therefore, the probability of occurrence \( y \) under \( z \) is

\[ p(y | z) = \int_{Q^{-1}(y)} p(\theta | z) d\theta = \int_{Q^{-1}(y)} \int_0^{+\infty} r_iCN(r_i e^{j\theta}; z; \sigma^2) dr_i d\theta. \]  

3.4 Analysis of the non-linear RF Chain Structures’ Power consumption

Non-linear MIMO systems complete amplitude/phase-detection directly in the RF domain. Since cumbersome demodulation is deleted, and no analog combination
of I/Q signals is required, their circuit power and costs are much less than the conventional RF-chain. The paper investigated the consumed power by every block from [88] and compared the consumed power between the conventional RF chain and the proposed updated non-linear RF chains in Fig.3.6. The power-saving from our proposed structures (the total consumed power is 4.135w) could be reduced by 73.49% compared to the conventional RF chain (the total consumed power is 15.6w). That shows 1146.5 watts of circuit power will be saved in the massive MIMO system, which is equipped with over 100 antennas. If the upgraded version of phase detection, 1-bit resolution ADC[89], is further utilized, the consumed power of each RF link could be further reduced to 1.145 watts. Those new designs of RF chains make green communications probable on the side of low power consumption.

The above comparison shows that the non-linear RF receiver structure makes it possible to realize green communication. Therefore, a green communication system can be constructed by replacing the traditional receiver with a non-linear low-power RF receiver in the communication system. For example, in the three common communication scenarios of the IoV, as shown in Fig.3.7, Fig.3.8, and Fig.3.9, non-linear

<table>
<thead>
<tr>
<th></th>
<th>Total power consumption</th>
<th>ADC power consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional receiver RF link</td>
<td>15.6W</td>
<td>3W*2=6W</td>
</tr>
<tr>
<td>Traditional receiver RF link +1bit ADC</td>
<td>9.62W</td>
<td>10mW*2=20mW</td>
</tr>
<tr>
<td>MO RF link+high resolution ADC</td>
<td>4.135W</td>
<td>3W*1=3W</td>
</tr>
<tr>
<td>PO RF link+high resolution ADC</td>
<td>4.135W</td>
<td>3W*1=3W</td>
</tr>
<tr>
<td>PO RF link+1 bit ADC</td>
<td>1.145W</td>
<td>10mW*1=10mW</td>
</tr>
<tr>
<td>HPO RF link+high resolution ADC</td>
<td>4.135W</td>
<td>3W*1=3W</td>
</tr>
</tbody>
</table>

Figure 3.6 : Power consumption comparison among the conventional RF chain and the proposed new non-linear RF chains.
Figure 3.7: The scenario of vehicle to base station in IoV.

Figure 3.8: The scenario of vehicle to vehicle in IoV.

Figure 3.9: The scenario of vehicle to roadside units in IoV.
and power-efficiency RF receivers can be deployed to build a green vehicle networking ecosystem.

3.5 Chapter Conclusion

In response to the challenges posed by traditional linear receivers, this chapter proposes a new low-power receiver for green car networking communications. Three different low-complex, low-power receivers are proposed to improve the existing low-power receivers, named non-linear low-power RF receivers. This chapter modeled the mathematical system based on their specific structure, and their corresponding probability density functions are derived for the following chapters. Compared with traditional receivers, the power consumption of the non-linear receiver mentioned in this chapter is reduced by 73.49%, indicating that the non-linear low-power RF receiver can be applied to roadside communication units, communication vehicles, 5G base stations and various communication nodes. Furthermore, they can effectively realize the energy-saving and emission reduction requirements in the green vehicle networking ecosystem.
Chapter 4

Achievable Rate Analysis of High Energy-efficiency Non-linear MIMO for Internet of Vehicles

4.1 Introduction

Channel capacity is an important indicator to measure the performance of the communication system. In information theory, the channel capacity is numerically equal to the maximum value of mutual information between the channel input signal and the channel output signal [90]. The channel capacity is the maximum rate at which the channel can achieve error-free transmission and has essential theoretical guiding significance for the design of the actual system.

At present, traditional wireless communication’s channel capacity has been extensively studied. Compared with the traditional wireless MIMO system, the non-linear MIMO system needs to meet specific constraints, mainly including the amplitude or phase operation of the received signal, and this operation shows non-linear mathematically. Such constraints lead to differences between the achievable rate analysis of the non-linear MIMO system and the achievable rate analysis of the traditional wireless communication system. Most of the conclusions and observations of the traditional wireless communication system are no longer valid. Therefore, the achievable rate analysis results cannot be directly applied to non-linear MIMO systems, and analyzing the capacity of a non-linear MIMO system is extremely challenging.

The theoretical part of the non-linear MIMO system, namely the analysis of
the system’s achievable rate, has not been reported in the literature up to now. Combining non-linear detection with multiple antennas is a new technology, and its capacity limit is still unclear. The theoretical research of non-linear MIMO systems has become a new topic. At the same time, it is closely related to the future demand for low-cost, low-power solutions. This chapter will analyze the MIMO system’s achievable rate composed of the three non-linear receivers mentioned in Chapter 3, including magnitude-only MIMO, phase-only MIMO, and -phase MIMO. Besides, in this chapter’s theoretical research, this thesis assumes that the receiver can perfectly obtain channel state information or access the channel estimation results.

The rest of this chapter is organized as follows.

To facilitate efficient industrial applications, we redesign the RF chain in massive MIMO to reduce its power consumption and fabrication cost. By reducing power consumption and hardware cost, efficient CPS can be achieved with low maintenance cost and stable transmission.

The contributions of the chapter can be summarized as follows.

(1) We propose three non-linear RF link structures to address the issues of high power consumption and fabrication cost in IoV.

(2) Theoretical analysis and simulation results show that the designed RF structures can reach the traditional RF performance with increased antenna numbers with less overall power consumption.

(3) The trade-off between power consumption and the uplink achievable rate is analyzed in non-linear MIMO systems. The results show that our designed non-linear RF structures can achieve a gain of up to 2.3 times as much as the traditional receiver structure, which implies our RF structures could be used in future industrial production.

(4) When calculating the uplink achievable rate of the non-linear systems with
the non-analytical form of the probability density function, we proposed an Antithetic-Quasi Monte-Carlo (QMC) algorithm based on Halton’s low discrepancy sequences (LDS) for dealing with the multi-dimensional integration problem. The proposed algorithm is more efficient than the traditional Monte Carlo (MC) algorithm.

The remainder of this paper is organized as follows. Chapter 4.2 introduces the traditional linear MIMO system capacity calculation method. Chapter 4.3 gives the non-linear MIMO system uplink achievable rate calculation method from the perspective of mutual information and proposes an efficient Antithetic-Quasi Monte Carlo algorithm for the multi-dimensional integration problem. Chapter 4.4 reports some simulation results which reveal the performance of non-linear MIMO systems from four perspectives. Section 4.5 concludes.

4.2 Capacity Calculation of Linear MIMO System

4.2.1 Linear MIMO Reference Systems

The capacity of linear MIMO systems with a total transmit power constraint $P$ and perfect receive CSI has been characterized in [91]. For a stationary memoryless channel, the ergodic capacity is given by

$$C_{\text{lin}} = \varepsilon_H \left[\log \det \left( I_{NR} + \frac{SNR}{NT} HH^H \right) \right]$$

(4.1)

and the capacity achieving input distribution for i.i.d. Rayleigh fading is circularly symmetric complex Gaussian distribution, $s \sim CN(0, \sigma_s^2 I_{NT})$. The average SNR per receive antenna in (8) is defined as

$$SNR = \frac{P}{\sigma^2} = \frac{NT\sigma_s^2}{\sigma^2}$$

(4.2)
4.3 Capacity Calculation of Non-linear MIMO System

The proposed new non-linear structure systems, which we mentioned above, can significantly save power consumption. However, the non-linear MIMO systems’ characteristics that lose half of the dimensional information will lead to some of the performance decreasing. In this part, we intend to explore the performance of the new structure system from the perspective of information theory via the uplink achievable rate of these non-linear MIMO systems. Besides, due to the problem of high-dimensional integration in the calculation process, we propose an efficient solution named Antithetic-QMC based on the Halton’s LDS method that can significantly speed up the calculation efficiency.

4.3.1 Achievable Rate of Non-linear MIMO System

We compute the achievable rates instead of capacity since the capacity of the non-linear MIMO systems are too cumbersome to find. The key characteristic in our non-linear MIMO systems are that the received signal $y$ at BS side is missing half the dimensions information after non-linear detector $g_{H_{non-linear}}(\cdot)$ process. Since we are considering a MIMO system, we need to consider the number of receiving antennas when calculating the achievable rate of the system. The probability of the output $y$ conditioned on $z$ plays a crucial role. Since the noise vector $w$ is white across the receive antennas and the nonlinear function $g_{H_{non-linear}}(\cdot)$ acts on each antenna separately, the conditional distribution of $y$ given $z$ can be factorized as

$$f(y|z) = \prod_{i=1}^{N_R} f(y_i|z_i),$$  \hspace{1cm} (4.3)

where $N_R$ denotes the number of receiving antennas, $y_i$ and $z_i$ denote the $i$-th elements in the real vector $y$ and the complex vector $z$, respectively. $r \sim CN(z, \sigma_w^2 I_{N_R})$ when $z$ is given.

Since we assumed that the channel $H$ is memoryless, the capacity is given by the
maximum mutual information between the channel input $s$ and the detector output $y$. Furthermore, since $H$ is known to the receiver, the channel output is the pair $(y,H)$. The mutual information can be written as

$$ I(s;y,H) = \varepsilon_H [I(s;y,H = H)]. \quad (4.4) $$

From (3.1), we obtain that $s$ and $H$ are statistically independent. We can observe that $s$, $z$ and $y$ constitute a Markov chain $s \to z \to y$ under a given channel realization $H = H$. Because $s$ and $y$ are conditionally independent, (4.4) can be upgraded to

$$ I(s;y|H) = \varepsilon_H[I(z;y|H = H)], \quad (4.5) $$

where according to the information theory, the mutual information of interest $I(z;y|H)$ is extended to

$$ I(z;y|H) = h(y|H) - h(y|z,H) $$

$$ = - \int f(y|H) \log (f(y|H)) \, dy $$

$$ + \iint f(z,y) \log (f(y|z)) \, dy \, dz. \quad (4.6) $$

From (4.5) to (4.6), the fact of $h(y|z,H) = h(y|z)$ is used. In order to calculate the mutual information of interest $I(z;y|H)$, the PDFs $f(y|H)$ and $f(y|z)$ are needed.

Given $f(y|z)$, $f(y|H)$ can be rewritten as

$$ f(y|H) = \int f(z|H)f(y|z,H) \, dz $$

$$ = \int f(z|H)f(y|z) \, dz. \quad (4.7) $$

Combining (4.6) and (4.7), we have
\[
I(z; y|H) = - \int f(y|H) \log \left\{ \int f(z|H)f(y|z)dz \right\} dy \\
+ \iint f(z, y) \log (f(y|z)) dy dz.
\] (4.8)

where \(f(y|z)\) is computed by (4.3) and (3.3), (3.7) - (3.9).

Remark: Deriving the expression of \(f(y|H), f(z, y)\) and \(f(z|H)\) is nontrivial. Instead of trying to explore the analytical expression of them, we evaluate (4.12) by the idea of stochastic simulation sample mean algorithm such as Monte Carlo (MC).

MC approximate \(f(y|H), h(y|H)\) and \(h(y|z)\) by

\[
f(y|H) \simeq \frac{1}{M} \sum_{j=1}^{M} f(y_i|z_j),
\] (4.9)

\[
h(y|H) \simeq - \frac{1}{N} \sum_{i=1}^{N} \log (f(y_i)),
\] (4.10)

\[
h(y|z) \simeq - \frac{1}{N} \sum_{i=1}^{N} \log (f(y_i|z_i)),
\] (4.11)

respectively, where \(z_j\) as the MC samples are generated according to complex Gaussian distribution \(\mathcal{CN}(0, \sigma^2 z H H^H)\). Combining (4.3), (4.12), (4.9) - (4.11). We approximate the achievable rate for non-linear MIMO as

\[
I(z; y|H) \simeq - \frac{1}{N} \sum_{i=1}^{N} \log \frac{1}{M} \sum_{j=1}^{M} \prod_{k=1}^{N_R} f(y_{i,k}|z_{i,k})
\]

\[
+ \frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{N_R} \log f(y_{i,k}|z_{i,k}).
\] (4.12)

Finally, averaging (4.9) - (4.11) over many different channel response \(H\), we can obtain the mutual information in (4.4).
4.3.2 Anti-Quasi Monte Carlo method

In this section, we will answer why we need to use QMC sampling to calculate multi-dimensional integrals instead of traditional MC sampling methods. Also we give the details of QMC and antithetic variates method to calculate the mutual information of interest $I(z; y|H)$ in HPO MIMO system.

As can be seen from formula (4.12), to calculate the achievable rate of the HPO MIMO system, we have to make two sampling approximations for the first term and one sampling approximation for the second term. Also, a subtraction operation is made after the above sampling approximations. As we knew, the MC sampling principle is to achieve an infinitely close to multi-dimensional integral by increasing the sampling point density, which means the more numbers of sampling points, the higher the accuracy of the multi-dimensional integral approximation. In our simulation, to obtain a stable achievable rate, the number of sampling points is at least 10,000. Therefore, our simulation requires at least 10,000*10,000 times to obtain smooth convergence. The above summarizes only under the case of the single input single output (SISO) situation. If the situation is extended to a multi-dimensional MIMO scenario, the number of simulation will increase drastically as the growth of antenna array numbers. This will make computational efficiency very low. Therefore, to increase the efficiency of multi-dimensional integration calculation becomes very necessary and essential in the non-linear MIMO system.

4.3.3 Monte Carlo

We consider MC method to calculate an integral problem, such as formula (4.10), (4.9) and (4.11) in Section II. We assume $f(\cdot)$ is an integral function on the unit cube $C^q = [0, 1]^q$ with $q$-dimension. In order to calculate integral $I(f)$ as follows[92]
we first extract random samples \( P_k = \{x_k : 1 \leq k \leq K\} \) from \( C^q \) which obeys uniform distribution \( U[0, 1]^q \). Then we calculate an estimate \( \hat{I}_K \) of \( I(f) \) by the following formula:

\[
I_K(f, P_k) = \frac{1}{K} \sum_{k=1}^K f(x_k). \tag{4.14}
\]

The key point of the MC method is that it is necessary to extract an independent, uniformly distributed random sequence in \( C^q \). Since a certain algorithm generates such a random sequence, it also can be called the pseudo-random sequence. According to the law of large numbers, \( I_K \) converges to \( I(f) \) in probability.

Let \( \sigma_f = \sqrt{Var[f(P_k)]]} \), where \( Var \) denotes variance. By the central limit theorem, the integration error produced by the MC satisfies the following inequality

\[
|I(f) - I_K(f, P_k)| \leq z_{\alpha/2} \frac{\sigma_f}{\sqrt{K}} \tag{4.15}
\]

with probability approximate \( 1 - \alpha \), where \( z_{\alpha/2} \) denotes the \( \alpha/2 \) quantile of Gaussian distribution \( \mathcal{N}(0, 1) \). Therefore, the convergency rate of MC method is \( \mathcal{O}(1/\sqrt{K}) \).

**Quasi-Monte Carlo**

Different from MC, QMC methods draw on number theory and abstract algebra. The basic idea of QMC methods is to replace the pseudo-random sequences in MC with low discrepancy sequences (LDS) or quasi-random sequences which are more uniform than random sequences. To measure the uniformity of a sequence, we introduce the following definition.

**Definition 1.** Let \( \mathbb{B} \) be a collection of all rectangles in \( [0, 1]^q \) with the form \( \prod_{j=1}^q [u_j, v_j], 0 \leq u_j \leq v_j \leq 1 \) and let \( m(B) \) be the volume of \( B \). The discrepancy
$D_K$ of the point set $\{x_1, x_2, ..., x_K\}$ relative to $B$ is defined as

$$D_K = \sup_{B \in \mathcal{B}} \left| \frac{\# \{x_i \in B\}}{K} - m(B) \right|,$$

where $\# \{x_i \in B\}$ denotes the number of $x_i$ contained in $B$.

According to the law of iterated logarithms, if a sequence is random, the expectation of the discrepancy of the sequence is bounded by $\log \log K/\sqrt{K}$. In contrast, the discrepancy of many low discrepancy sequences such as Halton sequence is bounded by constant times $(\log K)^q/K$.

**Halton’ LDS**

Any non-negative integer $k$ can be constituted as the following form based on the prime number $b$:

$$k = d_j b^j + d_{j-1} b^{j-1} + ... + d_1 b + d_0,$$

where $d_i \in \{0, 1, ..., b-1\}, i = 0, 1, ..., j, b^j \leq k < b^{j+1}$.

We define the radical inverse function $\varphi_b(k)$ based on $b$ as follows:

$$\varphi_b(k) = \frac{d_0}{b^1} + \frac{d_1}{b^2} + ... + \frac{d_j}{b^{j+1}},$$

it’s easy to find for any integer $k \geq 0$, $\varphi_b(k) \in [0, 1]$.

To obtain Halton’ LDS $\{x_1, ..., x_m\}$ of length $m$ with $d$-dimensional, we take $d$ different prime numbers $b_1, ..., b_d$ as base. Then let $x_k = [\varphi_{b_1}(k-1), ..., \varphi_{b_d}(k-1)]^T$, where $k = 1, ..., m$. In fact, it is no need to generate the Halton sequence starting from $k = 0$. That is to say, for $d$ non-negative integers $n_1, ..., n_d$, the above sequence can be taken as $x_k = [\varphi_{b_1}(n_1 + k - 1), ..., \varphi_{b_d}(n_d + k - 1)]^T$. We can generate Halton’ LDS by the following algorithm.

Niederreiter[97] states that the discrepancy of Halton sequence satisfies that

$$D_K \leq c_q \frac{(\log K)^q}{K} + \mathcal{O} \left( \frac{(\log K)^{q-1}}{K} \right),$$

(4.19)
Algorithm 1: An algorithm for generating Halton’s LDS

Input: base \( b_1, b_2, ..., b_d, k \)

1. for \( i = 1 \) to \( d \) do
2. \( b_{ki} = 0; \)
3. \( j = 0; \)
4. for \( k \neq 0 \) do
5. \( b_{ki} = b_{ki} + \text{mod}(k, b_i)/b_i^{j+1}; \)
6. \( k = \text{floor}(k/b_j); \)
7. \( j = j + 1 \) end;
8. Output \( b_{ki}; \)

where \( c_q \) is a constant which only depends on dimension \( q \). (4.16) implies that the Halton sequence is significantly more uniform than a random sequence.

Error bound of QMC

The integration error produced by QMC satisfies the following Koksma-Halwka inequality.

\[
|I(f) - I_K(f, P_K)| \leq V(f)D_K, \quad (4.20)
\]

where \( D_K \) is the discrepancy of the sequence \( P_K \). The variation \( V(f) \) in (4.20) of \( f(x) \) in the sense of Hardy and Krause is defined as:

\[
V(f) = \sum_{k=1}^{s} \sum_{1 \leq i_1 < i_2 < ... < i_k \leq s} V^{(k)}(f; i_1, ..., i_k). \quad (4.21)
\]

If \( f(x_1, ..., x_s) \) is sufficiently differentiable, for all positive \( k \leq s \) and \( k \) integers \( 1 \leq i_1 < i_2 < ... < i_k \leq s \), define the quantity as follows:

\[
V^{(k)}(f; i_1, ..., i_k) = \int_{I_k} \left| \frac{\partial^k f}{\partial t_{i_1}...\partial t_{i_k}} \right| dt_{i_1}...dt_{i_k}. \quad (4.22)
\]
(4.21) and (4.22) imply that once $f(\cdot)$ is given, $V(f)$ would be a constant. Therefore, the integration error produced by QMC only depends on $D_K$. From (18), the convergency rate of QMC method based on Halton sequence is $O\left(\left(\frac{\log K}{K}\right)^{q-1}\right)$. Since $(\log K)^{q-1}$ can be absorbed into any power of $K$, the convergency rate of QMC method can be thought as near $O(1/K)$. Therefore, QMC methods accelerate convergence from $O(1/\sqrt{K})$ of MC methods to nearly $O(1/K)$.

Statisticians focus on how to construct the best low discrepancy (quasi-random) point sets[98], [99], [100], [101]. At the same time, variance reduction techniques[102] are widely studied from another side for improving the efficiency of such sampling methods. In our work, we combine the flexibility of variance reduction techniques with the characteristic of effectiveness and fast convergence of low discrepancy sequences. We not only use the Halton sequences as our low discrepancy point sets, but also combine antithetic variates technique as the variance reduction techniques, and the detail can be found in the following part.

\textit{Antithetic variates technique}

Antithetic variates is one of variance reduction techniques[103] for MC sample[104][105]. It attempts to reduce variance by introducing negative dependence between pairs of sampling points[106]. If $U$ is uniformly distributed over $[0, 1]$, then $1-U$ obeys uniform distribution, too. According to this principle, if we generate $U_1, ..., U_n$ as the first path, then we still can generate $1-U_1, ..., 1-U_n$ as the second path without changing the law of this simulation process. Antithetic variates technique reduce the variance based on the following fact

\[
\text{Cov}[U, (1-U)] = E[U(1-U)] - E[U]E[1-U] \\
= E[U - U^2] - E[U](1 - E[U]) \\
= E^2[U] - E[U^2] \\
= -D[U] < 0,
\]
where Cov[·, ·] denotes the covariance. In particular, for Gaussian distributions commonly used in telecommunications, antithetic variates can be implemented by pairing the sequences Y_1, Y_2, ... of independently and identically distributed (i.i.d.) $CN(0, 1)$ variables. The key characteristics of the antithetic variates technologies is that for each $i$, $Y_i$ and $\tilde{Y}_i$ have the same distribution, and all the pairs $(Y_1, \tilde{Y}_1), (Y_2, \tilde{Y}_2), ..., (Y_n, \tilde{Y}_n)$ are i.i.d.

The antithetic variates estimator $\hat{Y}_{AV}$ is the average of all $2n$ observations from the common distribution of $Y_i$ and $\tilde{Y}_i$,

$$\hat{Y}_{AV} = \frac{1}{2n} \left( \sum_{i=1}^{n} Y_i + \sum_{i=1}^{n} \tilde{Y}_i \right) = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{Y_i + \tilde{Y}_i}{2} \right), \quad (4.24)$$

the variance can be written as

$$\text{Var}[Y_i + \tilde{Y}_i] = \text{Var}[Y_i] + \text{Var}[\tilde{Y}_i] + 2\text{Cov}[Y_i, \tilde{Y}_i]$$

$$= 2\text{Var}[Y_i] + 2\text{Cov}[Y_i, \tilde{Y}_i] \quad (4.25)$$

$$< 2\text{Var}[Y_i],$$

because $Y_i$ and $\tilde{Y}_i$ have the same distribution, the variance of $Y_i$ and $\tilde{Y}_i$ are the same. The condition for antithetic sampling to reduce variance becomes

$$\text{Cov}[Y_i, \tilde{Y}_i] < 0, \quad (4.26)$$

therefore,

$$\text{Var}[\hat{Y}_{AV}] < \text{Var} \left[ \frac{1}{2n} \sum_{i=1}^{2n} Y_i \right]. \quad (4.27)$$

(4.24) implies that the efficiency of the MC method is increased after introducing an antithetic variate. This technique can also be applied in the QMC method.

**Antithetic-QMC method**

We combine antithetic variates technique and QMC method and propose the Antithetic-QMC method to calculate uplink achievable rate for non-linear MIMO systems. We develop Antithetic-QMC algorithm as follows:
Algorithm 2: Antithetic-QMC algorithm for calculating the uplink achievable rate for non-linear MIMO system

Input: $N_T, N_R, N_1, N_2, H, W, \phi_k, \rho_k, (k = 1, ..., N_R)$;

$S_{um11} = 0, S_{um12} = 0, S_{um2} = 0, S_{um31} = 0, S_{um32} = 0$

1. for $i = 1$ to $N_2$ do
2. Draw Halton sequence $y_{i,2}$ by Algorithm 1;
3. for $j = 1$ to $N_1$ do
4. Draw Halton sequence $y_{i,j,1}$ by Algorithm 1;
5. Compute $f(y_{i,j,1}|z_{i,j})$ and $f(y_{i,j,2}|z_{i,j})$ by (4.3);
6. $S_{um11} = S_{um11} + f(y_{i,j,1}|z_{i,j})$;
7. $S_{um12} = S_{um12} + f(y_{i,j,2}|z_{i,j})$;
8. until the last simulation;
9. $S_{um2} = S_{um2} + \log \frac{S_{um11} + S_{um12}}{2N_1}$;
10. $S_{um31} = S_{um31} + \log f(y_{i1}|z_i)$;
11. $S_{um32} = S_{um32} + \log f(y_{i2}|z_i)$;
12. until the last simulation;
13. Compute $h(y|H)$ by $-\frac{S_{um2}}{N_2}$;
14. Compute $h(y|z)$ by $-\frac{S_{um31} + S_{um32}}{2N_2}$;
15. Compute achievable rate by (4.12).
4.4 Simulation and Results

Simulation experiments from four aspects are provided to confirm the previous parts in this section. Firstly, to illustrate that our non-linear MIMO systems can reduce total power consumption and are comparable to the traditional MIMO system’s performance, we compared them under the different dimensions of MIMO systems. Secondly, to clarify that our non-linear MIMO structures can achieve a good balance between low power consumption and high performance, we compared the power efficiency between traditional MIMO systems and non-linear MIMO systems. Thirdly, to verify the computational efficiency of our Antithetic-QMC algorithm based on Halton’s LDS, we compared the traditional MC and QMC algorithms from the perspective of the convergency rate under the same parameters. Finally, we found that in non-linear MIMO systems, different from the convention MIMO system, the Gaussian distribution as signaling does not optimize the system’s capacity. Instead, the skew-normal distribution as signaling can achieve better performance than the Gaussian distribution.

4.4.1 Comparison of Uplink Achievable Rate between Traditional MIMO System and Non-linear MIMO System

Fig.4.1 shows the uplink achievable rate of three types of nonlinear MIMO systems by comparison with traditional MIMO system, including MO-MIMO represented by the green line, PO-MIMO represented by the blue line, and HPO-MIMO represented by the pink line. We show the above simulation results under different MIMO scales situations. It can be observed from figure: 1. PO-MIMO system is the best performance among the three types of nonlinear MIMO systems, followed by MO-MIMO, and last HPO-MIMO. They account for 60% – 67%, 49% – 58% and 45% – 50% of their corresponding traditional MIMO scale performance, respectively. 2. As the dimension changes from 1*1 to 3*3 to 8*4, we can find that nonlinear
Figure 4.1: Comparison of uplink achievable rate between nonlinear MIMO system and traditional MIMO system at different MIMO scales.

MIMO can achieve system performance closer to traditional MIMO system. In other words, nonlinear MIMO technology has a promising industrial future in large-scale low-power communication systems due to its low cost and low power consumption characteristics of nonlinear devices.

4.4.2 Comparison of Power Efficiency between Traditional MIMO System and Non-linear MIMO System

Fig. 4.2 shows the power efficiency comparison between three non-linear MIMO systems and traditional MIMO systems, which can directly reflect the trade-off between power consumption and performance. Receiver power efficiency factor \( \eta = \frac{R}{N_R \cdot P_{RF}} \) is used to reflect the relationship between achievable rate and power consumption, where \( R \) represents the achievable rate of the MIMO system calculated in Equation (4.5), \( N_R \) stands for the receiver antennas number, and \( P_{RF} \) represents...
Figure 4.2: Power Efficiency Comparison between nonlinear MIMO system and traditional MIMO system under 4*4 MIMO.

The power consumed by the RF chain hardware circuits architecture. The calculation method of the traditional RF link power consumption of the MIMO system can be observed from Fig.3.1(a), that is, \( P_{RF} = P_{LNA} + P_{MIX} + P_{RF-sys} + P_{VCO} + P_{QVCO} + P_{PLL} + P_{ADC} \). Non-linear MIMO RF chain’s power consumption as shown in Fig.3.1(b) can be calculated as \( P_{RF} = P_{LNA} + P_{non-linear} + P_{ADC} \). Fig.4.2 shows the power efficiency comparison between non-linear MIMO and traditional MIMO under the 4*4 MIMO system. It can be observed from the figure that all three types of non-linear MIMO systems have higher power efficiency than the traditional MIMO system, and as the SNR ratio increases, the increase is more significant. Among them, the PO-MIMO system has the best performance, which is 2.3 times that of traditional MIMO, and MO-MIMO can also achieve an effect of approximately two times. Combined with the simulation of Fig.4.1, it can be found that the theoretical
superiority of the non-linear system. These two simulations provide a theoretical basis for the use of non-linear systems in the industry.

4.4.3 Convergence rate of QMC algorithm in nonlinear MIMO system

![Figure 4.3: Distributions of 4 points in two dimensions. The unit square is divided into 4 parts as shown on the left and 16 parts as shown on the right.](image)

Figure 4.3 : Distributions of 4 points in two dimensions. The unit square is divided into 4 parts as shown on the left and 16 parts as shown on the right.

To test the uniformity of Halton’ LDS, we implement algorithm 1 and compare distributions of $N_1 = 4$ (Fig. 4.3) and $N_2 = 16$ (Fig. 4.4) points on a unit square $n = 2$ given by two different sampling techniques: MC and Halton’ LDS. This provides a qualitative picture of the uniformity properties of these sampling techniques. In the first case, the unit square is divided into 4 and $4^2$ squares of measure $1/4$ and $1/4^2$, respectively. In the second case, the unit square is divided into 16 and $16^2$ squares of measure $1/16$ and $1/16^2$, respectively. Fig. 4.3/ Fig. 4.4 (c), (d) show 2-dimensional distributions of Halton’ points, and each of the 4 small squares contains exactly one
Figure 4.4: Distributions of 16 points from two dimensions. The unit square is divided into 16 parts, as shown on the left and 256 parts, as shown on the right.
Halton’ point. Random sampling MC (Fig. 4.3/ Fig. 4.4 (a), (b)) do not possess either of these properties.

Figure 4.5: Distributions of 64 points in two dimensions. The unit square is divided into 64 parts, as shown on the left and 4096 parts, as shown on the right.

Fig. 4.5 shows distributions of 64 points in two dimensions. From Fig. 4.5 (c), it is clear that each of the $64^2$ subsquares contains exactly 1 Halton’ point (Fig. 4.5 (d)). And this phenomenon is existing in all types of MC (Fig. 4.5 (a)) samplings: clustering and empty subsquares are clearly visible from these plots (Fig. 4.5 (b)). From Fig. 4.3 to Fig. 4.5, in summary it would appear that Halton’ LDS sampling gives a better way of arranging $N$ points in $n$ dimensions than MC method.

Furthermore, we extracted 2000 points from the two-dimensional unit square using the MC method and the Halton’ LDS, respectively. From Fig. 4.6, we can see that the points using the Halton’ LDS method are more uniformly, whereas
the points using the MC sampling method are denser in some places and sparse in others. Fig. 4.6 shows that Halton’ LDS has smaller standard error than MC.

<table>
<thead>
<tr>
<th>Method</th>
<th>Monte Carlo (MC)</th>
<th>Halton’ LDS</th>
</tr>
</thead>
<tbody>
<tr>
<td>The sequence method</td>
<td>Pseudorandom sequence</td>
<td>Low-discrepancy sequence</td>
</tr>
<tr>
<td>(Halton sequence)</td>
<td></td>
<td>(Halton sequence)</td>
</tr>
<tr>
<td>The distribution of the sampling points</td>
<td><img src="image1" alt="Monte Carlo" /></td>
<td><img src="image2" alt="Halton LDS" /></td>
</tr>
</tbody>
</table>

Figure 4.6: Monte-Carlo (MC) v.s. the Halton’ LDS under same simulation duration. In our simulation, the number of simulation is $10 \times 10,000 \times 10,000$.

To test the efficiency of the Antithetic-QMC method, we implement algorithm 2 and compare Antithetic-QMC with MC and QMC. MC and QMC for computing achievable rate of HPO MIMO can be implemented by modifying algorithm 2. The MC estimate $\hat{I}$ converges to the true value of $I$ as sample points $N$ approaches to infinity by the law of large numbers. Therefore we calculate the accurate value of $I$ by MC method. A comparison of methods requires a figure of merit. For sampling-based methods, standard error is an appropriate figure of merit [107]. As our figure of merit, we take log 2 of standard error $\delta$, where $\delta = \sqrt{\sum_{i=1}^{N}(f(x_i) - I(N))}$. The smaller log 2$\delta$, the higher efficiency of calculating.

Fig. 4.7 compares the log 2 of standard error among MC, QMC and Antithetic-QMC for calculating the achievable rate for HPO MIMO systems with simulation trials $N = 100, 1000, 5000$ and $10000$, respectively. The reason for the choice of
10000 as the limit is that in the variance reduction technique, the standard error $\delta = 0.02$ marks the result of the sampling method close to the multi-dimensional integral result. Fig. 4.7 shows that QMC converges fast, and the standard error is significantly smaller than MC. Antithetic-QMC further increases the convergency rate compared to QMC.

The performance of Antithetic-QMC is slightly better than QMC at a high number of samples. However, these two methods have much better performance than traditional MC methods, especially at higher sampling numbers. This is precise because both of these QMC methods use a more uniform LDS sequence instead of a random sequence in calculating the multi-dimensional integration in the HPO MIMO system. We can conclude that Antithetic-QMC is superior to QMC and MC in calculating uplink achievable rate for HPO MIMO system.
4.4.4 Skew Normal Distribution in Non-linear MIMO system

It is known from Shannon’s theorem that the distribution of the Gaussian signal can maximize the mutual information of the system in regular communication. However, the problem is whether this conclusion is still obeyed in the non-linear MIMO systems after non-linear distortion. This question will be answered from Fig.4.8. In conventional MIMO system, $s \sim \mathcal{CN}(0, \sigma^2_s I_{N_T})$ obeys the Gaussian distribution in (3.1). In our non-linear MIMO systems, we change the distribution from the Gaussian to skew-normal based on the PDF of skew-normal

$$p(s) = \frac{1}{w\sqrt{2\pi}} e^{-\frac{(s-\mu)^2}{2w^2}} \left[ 1 + \text{erf} \left( \frac{\theta(s-\mu)}{w\sqrt{2}} \right) \right]$$

where $w$ is the scale parameter, $\mu$ is the location parameter and $\theta$ is the skew parameter.

Then the situation becomes $s$ obeying skew-normal distribution, and both $H$ and $w$ obeying the Gaussian distribution. After the non-liner operator $g(\cdot)$ has been taken, according to the central limit theorem, the received signal $y$ at BS side can be approximated as a Gaussian distribution. With this conclusion, we can calculate the achievable rate of the non-linear systems under the skew-normal distribution. In order to find out which distribution can maximize the achievable rate of non-linear MIMO systems, we performed the simulation in simple SISO scenario. Besides, we use the HPO-MIMO system to represent the non-linear systems.

In Fig.4.8, we compare the achievable rates of SISO system under the different signaling: skew-normal distribution and different QAM modulation (256QAM, 64QAM, 16QAM and QPSK). To discuss which distributions can maximize the rates of HPO-MIMO, we compare them in the SISO scenario. The rates with skew-normal, which are computed with (4.6), (4.9) and (4.11), are compared with the Gaussian to verify their accuracy (when the parameter $\theta$ is equal to 0, the essence of skew-normal devolve to the Gaussian distribution). From the result, we observe that the skew-normal distribution can achieve better performance under some spe-
Figure 4.8: The achievable rates of HPO-SISO system under different distribution, including QAM modulation (uniform distribution), the conventional Gaussian distribution and the skew-normal distribution. The dotted line, the black and black dashed lines represent skew-normal distribution when the parameters $\theta = 4$, $\mu = 0$ and $\theta = 0, \mu = 0$ respectively. The solid blue line represents the Gaussian distribution as the reference. When the setting $\theta$ is 0, the essence of skew-normal is the Gaussian distribution.
cific values of the skew parameter $\theta$ than the corresponding Gaussian distribution. At each SNR stage, the achievable rate is always 0.3-0.5 bit/s/Hz more than its corresponding Gaussian distribution. The reason for that is HPO-MIMO suffers missing the magnitude information at the receiver. This result, in turn, can guide us to design the most appropriate constellation for a given SNR value under the non-linear MIMO systems.

Figure 4.9: The effect of different skew parameters $\theta$ on the mutual information of the HPO MIMO system, where $\sigma_s^2 = \sigma_w^2 = 0$ and $P_s = 0 dB$.

In Figure 4.9, we show the effect of different skew parameters $\theta$ on the mutual information of the HPO-MIMO system. (Among them, the skew parameter ranges from 0 to 1 with a step size of 0.05). In the previous part, we introduced the PDF of skew normal, from which we can derive its mean and variance as $E\{s\} = \mu + \omega \delta \sqrt{2/\pi}$ and $E\{|s - E\{s\}|^2\} = \omega^2 (1 - 2\delta^2 / \pi)$ respectively, where $\delta = \theta / \sqrt{1 + \theta^2}$. Then we can calculate the mutual information of the HPO-MIMO
system under different skew parameters \( \theta \) via formulas (3.1), (4.5), (4.9) and (4.11). We observe that with skew parameter \( \theta = 0.5 \), HPO-MIMO system can achieve the best performance. Fig. 4.9 once again confirms that the skew-normal distribution as the signalling can achieve a higher capacity \( I(z; y|H) \) in the HPO-MIMO system. This result explicitly shows that Gaussian distribution is not optimal for the non-linear MIMO system as the constraint. This finding also shows that in a non-linear system, we can design signaling by finding the optimal parameters of skew-normal to achieve a higher system achievable rate.

4.5 Chapter Conclusion

To make the MIMO technology more stable and cost-effective in the IoV, we have redesigned the energy-efficient MIMO systems comprising three types of different non-linear RF structures. These structures have the characteristics of low power consumption and low fabrication cost, and they can be easily applied to larger-scale industrial deployments. We verify the performance of these new types of energy-efficient structures from the perspective of information theory. Theoretical analysis and simulation results show that the designed RF structures can reach the traditional RF performance with increased antenna numbers but less overall power consumption. The trade-off between power consumption and the uplink achievable rate of non-linear MIMO systems also reveals that the non-linear RF structures increase the power efficiency by up to 2.3 times compared to the traditional receiver structure. We also provide an algorithm named Antithetic-QMC based on LDS for dealing with the multidimensional integration problem. Compared with the traditional MC algorithm, our algorithm is more efficient. Moreover, we reveal that when the skew-normal distribution is used as signaling, the non-linear MIMO systems can achieve better performance than the Gaussian distribution. In summary, this chapter provides the theoretical basis for applying the non-linear MIMO system
composed of the low-power RF receiver to the green vehicle networking ecosystem mentioned in Chapter 3.
Chapter 5

GMM-based Expectation-Maximization signal processing algorithm in HPO-MIMO system

5.1 Introduction

Chapter 3 and Chapter 4 discuss the non-linear low-power receiver structure and its corresponding system uplink achievable rate, respectively. This chapter aims to discuss signal processing issues when non-linear low-power receivers are used in the scenario of 5G base stations or vehicles in IoV. Among the three non-linear receivers, this chapter focuses on the HPO-MIMO system with the most complicated structure. The reason is that the current industry mainly uses π period phase detectors, such as the detection model AD8302. Besides, from an industrial perspective, designing this structure’s signal processing algorithm has more practical significance. Usually, signal processing algorithms need to achieve two goals: 1) low computational complexity and 2) high performance. Unfortunately, these two goals usually contradict each other: low computational complexity leads to a high bit error rate, and low bit error rate performance usually means high algorithm complexity.

Receiver detection algorithms in traditional wireless communication systems are usually divided into two categories: one is linear zero-forcing (ZF) algorithm [108] [109] [110] [111], minimum mean square error algorithm (MMSE) [112]; the other is non-linear spherical decoding (SD) [113], approximate message passing (AMP) [114] [115] and Maximum Likelihood Algorithm [116] [117] [118] [119]. Generally speaking, non-linear algorithms have a low bit error rate but extremely high complexity, while linear algorithms have low complexity but a high error rate. However, in the non-linear
MIMO system, due to the non-linear distortion of the signal at the receiving end, the practical receiver algorithms in the traditional wireless communication system almost lose their all effectiveness.

In the field of non-linear MIMO, the literature [120] starts from the Bayesian theory by reducing the channel estimation problem and multi-user detection problem into general linear mixed problems and using Generalized Approximate Message Passing (GAMP) algorithm solution. However, because there is no closed expression for the mean and variance of the phase observations, this work uses importance sampling technology to solve the problem, and its convergence rate becomes unstable. In some cases, the algorithm has serious divergence problems. Besides, from the perspective of non-convex optimization, the literature [121] solves the channel estimation problem and the multi-user detection problem through the shifting power (SPW) method, specifically the channel estimation the multi-user detection problem. The detection problem could be transformed into a non-convex optimization problem and can be solved by calculating the eigenvector corresponding to its smallest eigenvalue. However, this algorithm’s effect is not obvious in the case of high signal-to-noise ratio (SNR), and the algorithm itself has poor convergence.

In statistical calculations, the expectation-maximization (EM) algorithm [122] was originally designed to solve the problem of parameter estimation in the absence of data. The basic idea is first to estimate the value of the model parameters based on the observation data that has been given, and then based on the value of the missing data estimated in the previous step, and then re-combined the missing data with the previously observed data based on the estimated missing data. The parameter value is estimated again. Iteratively until the last convergence, the end of the iterative process.

In the HPO-MIMO system in this chapter, the observation value loses the phase
information of the amplitude information, and the EM algorithm can naturally solve it. However, in the HPO-MIMO system, the amplitude must be integrated from 0 to positive infinity through its probability density expression due to the distribution of observations. Unfortunately, it is difficult to obtain the integral, and it is urgent to design an algorithm to obtain the distribution of $\pi$-phase observation.

In response to the above problems, this chapter proposes an EM iteration channel estimation and multi-user detection algorithm based on the Gaussian mixture model (GMM) [123]. Specifically, the GMM algorithm is used to estimate the $\pi$-phase observation terminal distribution, and then the EM algorithm is used to estimate the signal to be recovered. Under this framework, GMM-EM type channel estimator and multi-user detector are designed for HPO-MIMO.

The key contributions of this chapter can be summarized as follows.

(1) In HPO-MIMO system, transformed the channel estimation (CE) and multi-user detection (MUD) problems to the generalized linear mixed problems under $\pi$-phase observations. Then the GMM-based EM algorithm is proposed to solve this generalized linear mixed problem. Besides, this chapter design the GMM-EM channel estimator and multi-user detector for HPO-MIMO.

(2) For the problem of phase ambiguity and amplitude ambiguity in the HPO-MIMO system, a new architecture is proposed, and the ambiguity problem can be solved by the least square method.

The rest of this chapter is organized as follows.

Chapter 5.1 introduces the $\pi$-phase MIMO system architecture. The signal transmission and reception of the channel estimation phase and the multi-user detection phase will be introduced in Chapter 5.2 and Chapter 5.3, respectively. Chapter 5.4 introduces the EM signal processing algorithm based on GMM. In Chapter 5.5, the proposed algorithm is simulated and compared with the previous work GAMP
algorithm. Chapter 5.6 concludes.

5.2 The system structure of HPO-MIMO

The system architecture is divided into two parts: the transmitting side and the receiving side. There are $U$ users at the transmitting side, and the base station is equipped with $N_r$ sub-antennas but has $N_r + 1$ radio frequency links. Unlike the traditional MIMO structure, the $N_r + 1$th RF link of this structure is a classic RF link with conventional I/Q structure, and the remaining $N_r$ links are $\pi$-phase with low noise amplifier (LNA), phase detector, and high-precision ADC RF link. Moreover, the radio frequency signal captured at the base station is separated into two parts by a power splitter with factor $A$, and then signals enter the $\pi$-phase radio frequency link and a linear combiner located on the classical I/Q frequency link for the further process.

First, introduce the structure of the transmitter. At the transmitter, a total of $U$ user equipment (UE) with a single antenna. Their RF link is designed as a classic I/Q structure transmitter. The coherence period is divided into two parts: the channel training sequence and data transmission. During this period, users will send orthogonal pilot sequences and QAM symbols, respectively. Single carrier (SC) transmission is implicitly assumed. The transmitted data frame is shown in Figure 5.2, where $\sqrt{p_u^t l_u} \in \mathbb{C}^K$ and $\sqrt{p_u^s x_u} \in \mathbb{C}^N$ represent pilot signals and QAM symbols, respectively, $p_u^t$ and $p_u^s$ indicates the transmit power of two different stages. $h_{n,u} \in \mathbb{C}^L$ represents the equivalent baseband channel response between the $N_r$-th base station antenna and the $u$-th UE, and $L$ is the number of channel taps. $H^l \in \mathbb{C}^{N_r \times U}$ represents the channel response matrix at the $l$th MIMO channel tap between the base station and the UE, where the $(N_r, u)$ item is $h^l_{n_r,u}$, which it is the $l$ element of $h_{n,u}$. On the $N_r + 1$th classical radio frequency link, the linear adder superimposes the analog radio frequency signals received on the $N_r$ $\pi$-phase radio
Figure 5.1: CE performance comparison under different trained length $k$. 
frequency links. Therefore, the equivalent channel between the $u$-th UE and the classic radio frequency link is expressed as $h_{0u} = \sum_{n=1}^{N} h_{n,r,u}$.

![Channel Training][Data Transmission]

Figure 5.2: CE performance comparison under different trained length $k$.

Next, this section will introduce the structure of the $\pi$-phase receiver. The system architecture is shown in Figure 5.1. The RF signal received from the transmitter passes through the $\pi$-phase receiver as follows. Take the $n_r$th RF link as an example, combined shown in Figure 5.1:

A. The receiver side receives the signal from the transmitter: the radio frequency signal captured by the $n_r$th antenna is expressed as $y_{n_r}^{RF}(t) = y_{n_r}^I(t) \cos(\omega_c t) - y_{n_r}^Q(t) \sin(\omega_c t)$, where $y_{n_r}^I(t)$ and $y_{n_r}^Q(t)$ represents the baseband signal received on the I/Q link, $y_{n_r}(t) = y_{n_r}^I(t) + jy_{n_r}^Q(t)$ is the equivalent complex envelope baseband signal, and $\omega_c$ is the carrier frequency.

B. Power splitter: The radio frequency signal is divided into two parts by the power splitter, $\alpha y_{n_r}^{RF}$ and $(1 - \alpha)y_{n_r}^{RF}$, then into the $\pi$ phase link and linear combiner respectively.

C. Linear combiner: The output of the linear combiner is $\sum_{n_r=1}^{N_r} (1 - \alpha)y_{n_r}^{RF}$. The output signal will be digitized by a classically structured radio frequency link. The observed digital baseband signal is $y_{conv}(nT_s) = \sum_{n_r=1}^{N_r} (1 - \alpha)y_{n_r}(nT_s)$, where $T_s$ is the baseband time domain sampling period determined by the signal baseband, and the sampling result will be used to eliminate the ambiguity problem in $\pi$-phase receiver. Section 5.4 concludes the details.

D. Low noise amplifier (LNA): After removing out-of-band interference through a band-pass filter (BSF), the RF signal after the nonlinear LNA $y_{n_r}^{RF}(t)$ becomes
\( \tilde{y}_{\text{RF}}(t) \), where \( \tilde{y}_{\text{RF}}(t) = \tilde{y}_I(t) \cos(\omega_c t) - \tilde{y}_Q(t) \sin(\omega_c t) \).

E. Phase detector: the radio frequency signal filtered by a nonlinear LNA and a BSF \( \tilde{y}_{\text{RF}}(t) \) transform \( \sqrt{\tilde{y}_Q^2(t) + \tilde{y}_I^2(t) \cos(\omega_c t + \phi(t))} \), where \( \phi(t) = \text{actan}(\tilde{y}_Q(t)/\tilde{y}_I(t)) \). Based on the basic principle of the phase detector, the phase \( \phi(t) \) is converted into a continuous voltage signal, and its amplitude is linearly proportional to the phase value, as shown in Figure 5.3.

F. High-precision ADC: The ADC samples the continuous voltage signal, and the result will be transmitted to the baseband processor for subsequent baseband processing.

\[ V_{\text{max}} \]
\[ -\frac{\pi}{2} \]
\[ 0 \]
\[ \frac{\pi}{2} \]
\[ \frac{3\pi}{2} \]
\[ -V_{\text{max}} \]
\[ \cdots \]
\[ \cdot \cdot \cdot \]

Figure 5.3 : Typical response curve of \( \pi \)-period phase detector.

5.3 Signal transmission and reception of Channel estimation (CE) / multi-user detection (MUD)

5.3.1 Signal transmission and reception of CE

In the CE stage, multiple users simultaneously transmit their own training sequences, which are designed to be orthogonal to each other. Due to the system
circuit structure’s difference, the signal reception on the $\pi$-phase (HPO) radio frequency link and the signal reception on the classical I/Q link will be discussed separately.

On the $n_r$-th $\pi$-phase RF link, before the phase detection, after removing the cyclic prefix (CP), the received observations are:

$$u_{n_r}^{CE} = \alpha T h_{n_r} + w_{n_r}^{CE}, n_r = 1, 2, \ldots, N_r,$$  \hspace{1cm} (5.1)

where $h_{n_r} = [h_{n_r,1}^T h_{n_r,2}^T \cdots h_{n_r,U}^T]^T$, $w_{n_r}^{CE}$ is Gaussian white noise, $T = [T_1 T_2 \cdots T_U]$, is a cyclic Toeplitz matrix with the size of $K \times K$ preserved the first $L$ columns of $\text{toep} \left(\sqrt{P_t} u_t, K\right)$, where $\text{toep} \left(\cdot\right)$ represents a Toeplitz matrix, and its construction method can be found in [30].

Next, the phase detector performs component processing on $u_{n_r}^{CE}$. The processing process is as follows, for example, $u_{m}^{CE}$ represents the $m$th element of $u_{n_r}^{CE}$. It is expressed as $r_m^{CE} e^{i \theta_m^{CE}}$ in the polar coordinate system. After the phase is extracted, the amplitude information $r_m^{CE}$ is completely lost, and the phase is preserved $\theta_m^{CE} = \angle \left( u_m^{CE} \text{ right} \right)$ as the $m$-th phase observation $y_m^{CE}$. In general, the total observation can be expressed as:

$$y_{n_r}^{CE} = \angle \left( \alpha T h_{n_r} + w_{n_r}^{CE} \right), n_r \in (1, 2, \ldots, N),$$ \hspace{1cm} (5.2)

where $y_{n_r}^{CE} = [y_1^{CE} y_2^{CE} \cdots y_K^{CE}]^T$, $\angle \left( \cdot \right)$ means do the $\pi$ phase operation for their vector elements.

Unlike $n_r$ $\pi$-phase links, the classical RF link is represented as the 0th link in this article. Except for the noise, it does not cause any distortion in the measurement of the complex envelope. Therefore, it receives the complete observation:

$$y_0^{CE} = (1 - \alpha) T h_0 + w_0^{CE}.$$ \hspace{1cm} (5.3)
The SNR during CE can be defined as:

\[
SNR_{CE} = 10 \log_{10} \left( K \sum_u p_{t,u} / (U \sigma^2) \right). 
\]  

(5.4)

So far, the CE problem can be conclude: how to reconstruction \( h_{n_r} \) base on the \( \pi \)-phase observations \( \{y_{n_r}^{CE}\}_{n_r=1}^{N_r} \) and the complete observations \( y_0^{CE} \)?

### 5.3.2 Signal transmission and reception of MUD

This chapter focuses on the baseband communication between the receiver and the UE, taking the single carrier symbol as an example. According to Figure 5.2, a single carrier symbol can be divided into two parts: a data part and a cyclic prefix (Cyclic Prefix, CP) part. The CP part will be used to eliminate inter-symbol interference. The data part contains \( N \) M-QAM symbols located in the QAM alphabet:

\[
A = A \times \{ \pm (2k_R - 1) \pm i (2k_I - 1), k_R, k_I \in \left[ \sqrt{M}/2 \right] \}.  
\]  

(5.5)

The received signal of the \( \pi \)-phase radio frequency link will be discussed as followed. Before the phase detection, the received observation after removing the CP of the \( n_r \)-th \( \pi \) phase link is:

\[
u_{MUD}^{n_r} = \alpha H_{n_r} x + w_{MUD}^{n_r}, n_r = 1, 2, \cdots, N_r,
\]  

(5.6)

where \( x = [x_1^T \ x_2^T \cdots \ x_U^T]^T \), noise function \( w_{MUD}^{n_r} \sim CN(0, \sigma^2 I_N) \) is additive Gaussian noise with variance \( \sigma^2 \). \( H_{n_r} = [\sqrt{p_{s,1}} H_{n_r,1} \ \sqrt{p_{s,2}} H_{n_r,2} \cdots \sqrt{p_{s,U}} H_{n_r,U}] \), and \( H_{n_r,u} = \text{rmtocp}(h_{n_r,u}, N) \) is a Toeplitz matrix with \( N \times N \) dimensions.

After phase detection, the phase observation at the \( n_r \)-th base station antenna is:

\[
y_{MUD}^{n_r} = \angle \pi (\alpha H_{n_r} x + w_{MUD}^{n_r}),
\]  

(5.7)

Combining equations (5.7) on \( n_r \in (1, 2, \cdots, N_r) \), the phase observation of the \( N_r \)th base station antenna is:
\[ y^{\text{MUD}} = \angle_x (aHx + w^{\text{MUD}}), \]  

(5.8)

where \( y^{\text{MUD}} = [y_1^{\text{MUD}} \ y_2^{\text{MUD}} \ \ldots \ y_{N_r}^{\text{MUD}}]^T \), \( H = [H_1^T \ H_2^T \ \ldots \ H_{N_r}^T]^T \),

\[ w^{\text{MUD}} = [w_1^{\text{MUD}T} \ w_2^{\text{MUD}T} \ \ldots \ w_{N_r}^{\text{MUD}T}]^T. \]

Unlike the signal received on the \( \pi \)-phase MIMO link, the traditional radio frequency link does not generate nonlinear distortion when receiving complex baseband observations. Therefore, the total observation value at the 0th radio frequency link (i.e., classic radio frequency link) is:

\[ y_0^{\text{MUD}} = (1 - \alpha)H_0x + w_0^{\text{MUD}}, \]  

(5.9)

The SNR during MUD is defined as: \( SNR_{\text{MUD}} = 10\log_{10} (\sum_u p_{s,u} / \sigma^2). \)

So far, the problem of MUD can be summarized as: how to recover QAM sequence \( x \) base \( \pi \)-phase observations \( y^{\text{MUD}} \) and complete observations \( y_0^{\text{MUD}} \)?

### 5.4 Signal transmission and reception of Channel estimation (CE)

In this chapter, the channel estimation problem (CE) and multi-user detection (MUD) problems in HPO-MIMO are modeled as generalized linear mixed problems under \( \pi \)-phase observation. Subsequently, the GMM algorithm is used to estimate the distribution of the \( \pi \)-phase observation, and then the EM algorithm is used to estimate the signal to be recovered to solve those mentioned above generalized linear mixing problem. Finally, GMM-EM type channel estimator and multi-user detector are designed for HPO-MIMO.
5.4.1 Convert CE and MUD problems into generalized linear mixed problems

Both CE and MUD problems in the HPO-MIMO system can be modeled as 
generalized linear mixed problems:

\[ y = \vec{g} (A s + w) = \vec{g} (z + w), \quad (5.10) \]

\( s \in \mathbb{C}^N \) is the known signal, \( A \in \mathbb{C}^{M \times N} \) is the signal to be reconstructed, and \( w \sim \mathcal{CN}(0, \sigma_w^2 I_M) \) represents additive complex Gaussian noise, \( z = As \) is the signal before noise. \( \vec{g} = [g_1 g_2 \cdots g_M]^T \) is a component operator, the \( m \)th element \( g_m \) corresponding to different types of radio frequency links is defined as:

\[
g_m(\cdot) = \begin{cases} 
1(\cdot), & \text{conventional RF link} \\
\angle(\cdot), & \text{HPO RF link}
\end{cases}, \quad (5.11)
\]

1(\cdot) means do not process the signal, that is, the output equals to its input signal.

5.4.2 EM signal processing algorithm based on GMM

The main calculation is divided into two parts. First, use the GMM algorithm to obtain the distribution of HPO MIMO observations \( y \), and then use the EM algorithm to obtain the estimated \( A \), so that the condition of the observed signal \( y \) probability \( P (s|y) \) has the largest log-likelihood.

The first step: the distribution of the observation value \( y \) in the formula (5.10) is fitted by the linear combination of the \( k \) sub-Gaussian distribution, and its distribution is as follows (\( x_j \) in the following formula represents the \( j \) observation value \( y \) in formula (5.10)):

\[
P_M (x_j) = \sum_{i=1}^{k} \alpha_i P \left( x_j | \mu_i, \sigma_i^2 \right), \quad (5.12)
\]
where $\mu_i$ represents the mean value of the $i$th sub-Gaussian, and $\sigma_i^2$ represents the variance of the $i$th sub-Gaussian. $\alpha_i = P(z_j = i)$ represents the weight of the $i$th sub-Gaussian occupying the $k$ sub-Gaussian distribution. Given that a sample $x_j$, the posterior probability of belonging to $i$ is:

$$
P(z_j = i|x_j) = \frac{P(z_j = i) P(x_j|z_j = i)}{\sum_l P(z_j = l) P(x_j|z_j = l)} = \frac{\alpha_i P(x_j|z_j = i)}{\sum_l \alpha_l P(x_j|z_j = l)}, \quad (5.13)$$

can be sampled as follows,

$$
r_{ji} = \frac{\alpha_i P(x_j|z_j = i)}{\sum_l \alpha_l P(x_j|z_j = l)}. \quad (5.14)$$

Calculate the corresponding $(\alpha_i, \mu_i, \sigma_i^2)$ in the formula (5.12) through the EM algorithm, and then the distribution of HPO-MIMO observation $y$ can be derived.

E-Step:

$$
r_{ji} = \frac{\alpha_i P(x_j|z_j = i)}{\sum_l \alpha_l P(x_j|z_j = l)}. \quad (5.15)$$

M-Step:

$$
\alpha_i = \frac{1}{n} \sum_{j=1}^n r_{ji}, \quad (5.16)
$$

$$
\mu_i = \frac{\sum_{j=1}^n r_{ji} x_j}{\sum_{j=1}^n r_{ji}}, \quad (5.17)
$$

$$
\sigma_i^2 = \frac{\sum_{j=1}^n (x_j - \mu_i)(x_j - \mu_i)^T}{\sum_{j=1}^n}. \quad (5.18)
$$

Iterate repeatedly until convergence.

The purpose of E-Step is to find the posterior probability of the observation $x_j$ generated by the $i$th sub-Gaussian distribution. The purpose of M-Step is to find the specific parameters in the formula (5.12) $(\alpha_i, \mu_i, \sigma_i^2)$. The derivation process can be solved by maximum likelihood, that is, let:

$$
L = \prod_{j=1}^n P_{M}(x_j) = \prod_{j=1}^n \left[ \sum_{i=1}^k \alpha_i P(x_j|\mu_i, \sigma_i^2) \right], \quad (5.19)
$$
By the logarithmic optimization formula (5.19), it can be derived as:

\[
L = \sum_{j=1}^{n} \log \left[ \sum_{i=1}^{k} \alpha_i P \left( x_j | \mu_i, \sigma_i^2 \right) \right] = \sum_{j=1}^{n} \log \left[ \sum_{i=1}^{k} \alpha_i \frac{1}{\sqrt{2\pi\sigma_i}} e^{-\frac{(x_j - \mu_i)^2}{2\sigma_i^2}} \right], \quad (5.20)
\]

Differentiate the \( \alpha_i, \mu_i, \sigma_i^2 \) in the formula (5.20), and then can get \( \alpha_i, \mu_i, \sigma_i^2 \) expression:

\[
\frac{\partial L}{\partial \mu_i} = \sum_{j=1}^{n} \alpha_i P \left( x_j | \mu_i, \sigma_i^2 \right) \frac{z_i - \mu_i}{\sigma_i^2} = \sum_{j=1}^{n} r_{ji} (x_j - \mu_i) = 0, \quad (5.21)
\]

\[
\frac{\partial L}{\partial \sigma_i} = \sum_{j=1}^{n} \alpha_i \frac{1}{\sqrt{2\pi}} \left[ \frac{1}{\sigma_i^2} e^{f} + \frac{1}{\sigma_i} e^{f} \left( \frac{(x_j - \mu_i)^2}{\sigma_i^2} \right) \right] = \sum_{j=1}^{n} r_{ji} \left[ (x_j - \mu_i)^2 - \sigma_i^2 \right] = 0, \quad (5.22)
\]

So far, the derivation is complete.

Step 2: Use the EM algorithm to obtain the \( A \) to be estimated so that the conditional probability \( P \left( s \mid y \right) \) of the observed signal \( y \) has the largest log-likelihood.

Objective function: The first term is the log-likelihood of \( P \left( y \mid s \right) \), and the second term is the log-likelihood of \( P \left( s \right) \).

\[
Q = \sum_{j=1}^{n} \sum_{i=1}^{g} \alpha_i \log C N \left( y_j; A s_j T, \sigma_i^2 \right) + \{ \log C N \left( s_j; \varepsilon, \Omega_i \right) \mid y_j \}, \quad (5.23)
\]

where \( z_iC N \left( \xi_i, \Omega_i \right), T = (A s_j)^{-1} \mu_i \), it should be noted that \( \mu_i \) here represents the mean value of the \( i \) sub-Gaussian in the formula (5.12), \( \alpha_i \) represents the weight of the \( i \)th sub-Gaussian occupies the \( k \) sub-Gaussian distribution. Next, use the EM algorithm to find the \( A \) to be estimated so that make sure \( Q \) is the largest.

E-Step:

\[
m_i = A^{-1} \mu_i + \gamma_i^T \left( y - \mu_i \right), \quad (5.24)
\]

\[
v_i = \left( I - \gamma_i^T A \right) \Omega_i + m_i \cdot m_i^T, \quad (5.25)
\]

\[
\gamma_i = \left( A \Omega_i A^T \right)^{-1} A \Omega_i, \quad (5.26)
\]
M-Step:

\[
A_{\text{max}} = \frac{\sum_{i=1}^{g} m_i (\sigma_i^2)^{-1} \cdot \alpha_i}{\sum_{i=1}^{g} v_i \cdot \alpha_i}.
\] (5.27)

Iterate repeatedly until convergence.

The E-Step’s purpose is to prepare for obtaining the signal \(A\) to be reconstructed in the next step by calculating the intermediate variables \(m_i\) and \(v_i\). The M-Step aims to obtain the derivative \(A\) by \(Q\), and make its derivative to 0, and then the \(A\) can be estimated.

The specific solution process is as follows:

Let formula (5.23) take the derivative of \(A\) and set its derivative to 0, then can get:

\[
A_{\text{max}} = \frac{\sum_{i=1}^{g} m_i (\sigma_i^2)^{-1} \cdot \alpha_i}{\sum_{i=1}^{g} v_i \cdot \alpha_i},
\] (5.28)

where \(m_i = E[p(a|y_i)]\) represents the mean value of \(p(a|y_i)\), \(v_i = E[p(aa^T|y_i)]\) represents \(v_i = E[p(aa^T|y_i)]\) variance, \(a = z_i T\), \(\alpha_i\) represents the first \(i\) in the formula (5.12). The sub-Gaussian occupies the weight of the sub-Gaussian distribution of \(k\).

The specific calculation expression is:

\[
m_i = A^{-1} \mu_i + \gamma_i^T (y - \mu_i),
\] (5.29)

\[
v_i = (I - \gamma_i^T A) \Omega_i + m_i \cdot m_i^T,
\] (5.30)

\[
\gamma_i = (A \Omega_i A^T)^{-1} A \Omega_i,
\] (5.31)

where \(\Omega_i\) represents the variance of \(z_i\) in formula (5.23).

So far, the problem of solving the unknown signal to be recovered in formula (5.10) is solved.
5.4.3 GMM-EM-CE channel estimator

According to formula (5.2), the channel estimation problem on the nrth HPO-MIMO radio link can be mathematically described as: How to recover $h_{nr}$ based on the phase observation $y_{n r}^{CE}$? This problem will be handled by the GMM-EM algorithm, replacing $x_j$, $g_m$, $s$ and $w$ in section 5.4.2 with formulas (5.10) in $y_{n r}^{CE}$, $\angle_{\pi}(\cdot)$, $aT$, and $w_{n r}^{CE}$, the channel estimation $h_{nr}$ can be solved.

However, due to the phenomenon of $\pi$ phase ambiguity and amplitude ambiguity at the observation in the HPO-MIMO system. Specifically, this is due to the existence of the $\pi$ phase detector $\angle_{\pi}(x) \equiv \angle_{\pi}(\gamma e^{j\theta}x)$ phenomenon. Where $x$ represents any complex number, $\gamma$ is a positive number, $\theta \in \{-\pi, \pi\}$, so the estimated result may have experienced amplitude stretching and phase flipping. To solve this problem, in the process of CE, the least square(LS) method is used for correction, and the specific method is as follows:

Fixing the results by the correction parameters $\beta_{nr} \in \mathbb{R}$, that is $\beta_{nr}\hat{h}_{nr}$ as the final estimated value of $h_{nr}$.

Where $\beta_{nr} \in \mathbb{R}$ is the positive or negative real number representing the amplitude and the phase ambiguity of the $n_r$th $\pi$-phase radio frequency link. By the definition of $\{h_{n r}\}_{n_r=0}^{N_r}$ and $\{h_{0u}\}_u$, we can get $h_0 = \sum_{n_r=1}^{N_r} bfh_{nr}$. Therefore exists,

$$\hat{h}_0 \approx B\beta, \quad (5.32)$$

where $B = \begin{bmatrix} \hat{h}_1 & \hat{h}_2 & \cdots & \hat{h}_{N_r} \end{bmatrix}$, $\beta = [\beta_1 \beta_2 \cdots \beta_{N_r}]^T$, since $\beta$ is a real number vector, the formula (5.32) can be equivalent to:

$$\hat{h}_0^e \approx B_e\beta, \quad (5.33)$$

where $\hat{h}_0^e = \Re\left(\hat{h}_0^T\right) \triangleq \text{left}(\hat{h}_0^T)^T$ and $B_e = [\Re\left( bfh \hat{B}^T \right) \Im\left( \hat{B}^T \right)]^T$, therefore $\beta$ can be approximated as $\hat{\beta} = (B_e^T B_e)^{-1}B_e^T \hat{h}_0^e$. So far, the ambiguity problem has been resolved.
That is to say, in the above-mentioned CE stage, the observation $y_0^{\text{MUD}}$ from a single classical radio link is used, and the problem of $\pi$ phase ambiguity and amplitude ambiguity can be eliminated through the LS algorithm.

5.4.4 GMM-EM-MUD multi-user detector

MUD process: Replace the above $x_j, g_m, A$ and $w$ with the formula (5.10) in the $[y^{\text{MUD}}_0 y^{\text{MUD}}_0]_T, \angle_\pi (\cdot \text{ right}), [\alpha H^T (1 - \alpha) H_0^T]_T$ and $[w^{\text{MUD}}_0 w^{\text{MUD}}_0]_T$ can solve the MUD signal $x$. It is worth noting that the first $N_r$ observations come from the $\pi$-phase RF link, and the last observation, the $N$th observation, comes from the traditional RF link. Therefore, the first $N_r$ link observations and the last link observation are respectively the operations of $\angle_\pi(\cdot)$ and $1(\cdot)$ for the received signal.

Unlike GMM-EM-CE, which has an amplitude and $\pi$-phase ambiguity problems, GMM-EM-MUD performs multi-user detection and the observation $y_0^{\text{MUD}}$ from the classical radio link has been involved in the recovery of QAM symbol $x$, and successfully eliminated the ambiguity. Therefore, there is no need to adopt amplitude and phase ambiguity processing methods in the MUD stage.

5.5 Simulation and Results

This chapter first analyzes the comparison of the channel estimation and multi-user detection performance of HPO-MIMO, PO-MIMO, and traditional MIMO based on the proposed GMM-based EM algorithm. Secondly, this chapter compared with the GAMP algorithm as the reference.

This chapter uses mean square error (MMSE) to evaluate channel performance, which is defined as $\frac{1}{N_r} \sum_{n_r \in [N_r]} \| \hat{h}_{n_r} - h_{n_r} \|^2$, where $\hat{h}_{n_r}$ is the estimation of channel response $h_{n_r}$.

In order to show the channel estimation performance of HPO-MIMO and PO-MIMO directly, the channel estimation performance of traditional MIMO is used.
as a reference in the simulation. In this section, two MIMO dimensions are set up, including 4*4 (Nr*Nt) and 8*4 (Nr*Nt). The power separation factor in Figure 5.1 is defined as $\alpha = \frac{N_t - 1}{N_r}$.

5.5.1 CE performance comparison among HPO-MIMO, PO-MIMO and traditional MIMO

This section will verify the proposed algorithm from the perspectives of different training sequence lengths $k$ and different SNR ratios. Figure 5.4 shows the CE performance for three types of MIMO under different training lengths of $k$. The MIMO dimensions are $N_t = 4$, $N_r = 4$, and $\text{SNR}_{CE} = 15dB$. It can be seen that as the length of the training sequence increases, the MSE values of the three different MIMO schemes all show a downward trend, because more observations are used for channel reconstruction. Therefore, it can be concluded that increasing the length of the training sequence can improve the performance of CE. Besides, it can be seen

![Figure 5.4: CE performance comparison under different trained length $k$.](image-url)
from Figure 5.4 that the CE performance of HPO-MIMO and PO-MIMO is not as good as that of traditional MIMO. When the training sequence length $k$ is fixed to 600, the MSE of HPO-MIMO, PO-MIMO, and traditional MIMO The values are -15.81dB, -16.38dB, and -19.64, respectively. Compared with traditional MIMO, HPO-MIMO has an SNR ratio loss of about 3.83dB. This is because compared to traditional MIMO with all amplitude observations, HPO-MIMO only obtains $\pi$-period phase observations. Compared with PO-MIMO, HPO-MIMO has an SNR ratio loss of about 0.57dB. This is because PO-MIMO can obtain observations of $2\pi$ period phases, which can obtain more information than HPO-MIMO. Finally, it can be observed from Figure 5.4 that as the training length $k$ increases, the MSE between HPO-MIMO and PO-MIMO gradually decreases. When the training length $k$ is 950, the gap between the two can be reduced to 0.31dB. It can be concluded that the phase ambiguity problem existing in HPO-MIMO can be reduced by transmitting a longer training sequence.

Figure 5.5: CE performance comparison under different SNR.
Figure 5.5 shows the comparison of three MIMO channel estimation performances under different channel SNR ratios. The MIMO dimensions are $N_t = 4$, $N_r = 8$, and $k = 1200$. It can be seen that as the channel SNR ratio continues to increase, the MSE values of the three different MIMO schemes continue to decrease because more accurate observations are used for channel reconstruction. Therefore, the first conclusion is that by improving the channel SNR ratio, the proposed algorithm’s CE performance can be improved. Secondly, it can be seen from Figure 5.5 that HPO-MIMO has an SNR ratio loss of about 4 to 7 dB compared to traditional MIMO. The reason for that is compared to traditional MIMO with all amplitude observations, HPO-MIMO only obtains $\pi$-period phase. Compared with PO-MIMO, HPO-MIMO has an SNE ratio loss of about 0.05 2.5dB. The reason for that PO-MIMO can obtain observations of $2\pi$ period phases, which can obtain more information than HPO-MIMO. Finally, by comparing the GAMP algorithm, it can be found that the proposed GMM-EM algorithm has a gain of 1-2dB. Furthermore, the convergence of the proposed GMM-EM algorithm is better than that of the GAMP algorithm.

5.5.2 MUD performance comparison among HPO-MIMO, PO-MIMO and traditional MIMO

Figure 5.6 shows the comparison of MUD performance between HPO-MIMO, PO-MIMO, and traditional MIMO. The MIMO dimension is $N_t = 4$, $N_r = 8$, $k = 1200$, and SNR$_{CE}$=15 dB. Due to missing amplitude observations and $\pi$ phase ambiguity, the MUD performance of HPO-MIMO is generally lower than that of traditional MIMO. Besides, due to the $\pi$ phase ambiguity problem, the MUD performance of HPO-MIMO is slightly lower than that of PO-MIMO. However, the bit error rate curves of HPO-MIMO and PO-MIMO are very similar to each other, which further reflects the potential of HPO-MIMO in practice.
Secondly, the comparison between the solid line ($N_r = 4$) and the dashed line ($N_r = 8$) in the figure shows that by using more antennas, the MUD performance of two MIMO’s schemes can be improved. This is because more base station antennas can provide more observations for QAM symbol recovery in the MUD. When the number of receiver antennas $N_r$ used is 4, the BER of HPO-MIMO reaches $10^{-3}$, and the SNR ratio for MUD is about 17dB. However, when the number of base station antennas used is 8, The SNR ratio required for MUD can reach the same BER as long as about 15.5dB. This means that by doubling the number of antennas at the receiver side, an SNR gain of approximately 1.5dB can be obtained. Besides, by comparing the GAMP and GMM-EN algorithms, it can be found that under the 4*4 MIMO, the BER of GAMP is exceptionally high, while the GMM-EM algorithm can reach more than $10^{-3}$ under the condition of high SNR, such as 15dB or more. This means the GMM-EM algorithm has better performance than the GAMP algorithm.
in the small-scale MIMO dimension.

5.5.3 The effect of different base station antenna’s distance on HPO-MIMO performance

In this section, we discuss how HPO-MIMO performance is affected by channel correlation on the receiver side. The distances between the antennas at the receiving side are $0.5\lambda$, $1.5\lambda$, and $3\lambda$, representing strong channel correlation, medium channel correlation, and weak channel correlation. $\lambda$ represents the wavelength of the transmitted signal. In this section, $k = 1200$, $\text{SNR}_{CE} = 15$ dB, and $N_t = 4$ are fixed.

![Figure 5.7: MUD performance comparison under different antenna distance.](image)

The simulation results are shown in Figure 5.7. The MUD performance of HPO-MIMO, PO-MIMO, and traditional MIMO gradually improves with the increase of the distance between the antennas, especially the distance between the antennas at the receiver side increases $0.5\lambda$ to $1.5\lambda$. This is because the channel correla-
tion attenuates as the distance between the antennas at the receiver side increases. However, compared with traditional MIMO, HPO-MIMO is more sensitive to channel correlation, followed by PO-MIMO. For example, when the distance increases from $0.5\lambda$ to $1.5\lambda$, the performance of HPO-MIMO increases the fastest, followed by PO-MIMO. When the distance between the antennas increases from $1.5\lambda$ to $3\lambda$, the BER of traditional MIMO has overlapped, but HPO-MIMO and PO-MIMO can still be distinguished, HPO-MIMO increases performance even more. However, if the receiver uses the traditional MIMO method, its MUD performance will not increase after the antenna spacing exceeds $1.5\lambda$. Besides, when the antenna distance is $3\lambda$, HPO-MIMO and PO-MIMO’s detection performance is relatively close, which means that the performance is caused by the phase ambiguity and by increasing the antenna distance amplitude ambiguity in the HPO-MIMO system can be compensated loss.

5.6 Chapter Conclusion

This chapter studies the GMM-based EM signal processing algorithm in the HPO MIMO system to solve the channel estimation problem and multi-user detection problem under $\pi$-phase observation. Firstly, the channel estimation problem and multi-user detection problem in HPO-MIMO are modeled as generalized linear mixed problems under $\pi$-phase observation. Since the observation signal suffers from the non-linear transformation, its distribution makes it impossible to obtain it directly. Subsequently, the GMM algorithm is used to estimate the $\pi$-phase observation distribution, and then the EM algorithm is used to estimate the signal to be recovered. Under this framework, GMM-type channel estimator and multi-user detector are designed for HPO-MIMO. Besides, a new architecture is proposed for the phase ambiguity and amplitude ambiguity problems in HPO-MIMO systems, and the ambiguity problem is solved by the least square method. Simulation results
show that the algorithm proposed in this chapter has high convergence and has better performance than the GAMP algorithm under a small-scale MIMO system.
Chapter 6

Conclusions

This thesis focuses on the non-linear MIMO transmission technology and high energy efficiency theory in the IoV. Specifically, applying the non-linear RF receiver structure with the characteristics of low-power consumption and low-cost to different communication nodes of the IoV, such as 5G base stations, roadside units, sensor nodes and communication vehicles, can fundamentally reduce the overall power consumption and operating cost of the IoV. Obtaining and transmitting urban environmental information and vehicle driving information on different low-consumption communication nodes can provide an information source for establishing V2V channel modeling based on real geographic location information. Besides, for the non-linear MIMO technology, this thesis discusses the uplink achievable rate and channel estimation, and multi-user detection.

1. Considering the challenges brought by the modeling of V2V channels in cities, the method of modeling V2V channels based on real geographic location information and vehicle driving environment information is studied. By using communication units deployed at various nodes in the city, the city environment information and vehicle driving information can be obtained and combined with any city’s map. Consequently, a real-time V2V channel model based on real geographic location information is proposed. This method adopts real geographic location information to construct a large-scale fading model and employs the vehicle’s environmental location information to construct a small-scale fading model. After obtaining the two connected vehicles’ relative moving speed, the Doppler shift can be modeled. The
geometric method is used to identify the types of multiple interactions between vehicles, such as reflection and diffraction. Based on the method, the R-Tree structure is introduced to increase the efficiency of the search. Experimental results show that the proposed method addresses the problem that the channel model does not fit the vehicular networks’ actual operating environment.

2. A structure design of the non-linear receiver for IoV communication was studied to address the problem of excessive high power consumption in the IoV. The non-linear low-power radio frequency (RF) receiver structure was proposed based on the replacement of the intermediate-frequency and high-frequency parts contained in conventional receiver by an amplitude or phase detection receiver. Such alternations solve the defect of excessive power consumption caused by the traditional receivers relying on In-phase/ Quadrature (I/Q) modulation. Moreover, we also further analysed the physical characteristics of the proposed low-power non-linear RF receivers, established three mathematical models of non-linear receivers and derived their probability density functions. The approach for deploying low-power non-linear RF receivers on infrastructure in urban environments, such as 5G base stations, roadside units, communication nodes, sensor networks, etc., to form a green and low-power IoV’s ecosystem were also presented in this thesis.

3. In view of the challenges imposed by the capacity of non-linear MIMO channels in the IoV, and considering that the MIMO system composed of non-linear receivers does not have closed solutions, a method for calculating the uplink achievable rate of non-linear MIMO systems is proposed using the mutual information theory. When calculating the uplink achievable rate, the conclusions are drawn from the previous chapter that ”due to the presence of reflected signals, the V2V channel can be regarded as a Gaussian channel in dense urban areas with a large number of buildings” is firstly used. Then the uplink achievable rates of three kinds of non-linear MIMO systems are analyzed in the case of Gaussian channels. Numer-
ical simulations are further carried out to verify the analysis. While deriving the
general calculation framework, an efficient Antithetic-quasi Monte Carlo algorithm
is proposed, which effectively solves the problem of high-dimensional integration.

4. In response to the non-linear MIMO receiver’s challenges in IoV, the Expectation-
Maximum (EM) algorithm based on the Gaussian Mixture Model (GMM) is used
to solve the channel estimation and multiuser detection problem under the \text{-phase}
observations. Firstly, the problem of channel estimation and multiuser detection in
Half Phase Only-MIMO (HPO-MIMO) is modeled as a generalized linear mixture
problem under \text{-phase observations. Secondly, the GMM} algorithm is used to merge
multiple Gaussian distributions with different weights to obtain the \text{-phase receiver
distribution. Then the EM algorithm is used for recovering the signal iteratively. Based on the proposed framework, the GMM-type channel estimator and multiuser
detector are designed for HPO-MIMO.
Chapter 7

Future Works

In this chapter, possible future research directions are discussed based on the works in this thesis.

1. In Chapter 2, this thesis applies different channel models in the LTE-V link-level simulation platform to obtain SNR-BLER data. Although the main work of link-level simulation is to provide physical layer data for the upper layer, for the channel modeling part, a set of real channel data acquisition equipment is still needed to verify the proposed channel’s accuracy by the ray-tracing method. The mentioned GWV2V uses the 5.9GHz frequency band (5.9GHz is a dedicated frequency band for LTE-V) and are not interfere with electronic signals from other communication equipment. However, perhaps this frequency band will be allocated to other signals soon, and it is still necessary to continue to study the influence of interference from other electronic devices.

2. In Chapter 3, in the green communication system of the urban vehicle network, it is assumed that all nodes deploy half of the receiving antennas and half of the transmitting antennas, and the non-linear receiver technology proposed in this thesis is used in the design of the receiving antennas. However, this thesis does not design the ratio of the receiving antenna to the transmitting antenna to differentiate the attributes of different nodes.

3. In Chapter 4, there is no theoretical proof of what kind of distribution can be used as the input signal to make the non-linear MIMO system get the best uplink achievable rate. This thesis only observed that the skew-normal distribution as
the input could obtain the best performance in the limited simulation comparison. Therefore, it is still an open question to explore which distribution can maximize non-linear MIMO’s performance.

4. In Chapter 5, more complex multi-cell scenarios should also be discussed in the future. At this time, the interference from other cells should be considered.

In general, in the era of “Internet +”, a large number of low-power radio frequency receivers will be deployed on the infrastructure of the IoV, which brings many opportunities and challenges for future green wireless communications. It is believed that this “new infrastructure” model can be used to promote the construction of a green vehicle networking ecosystem in the future.
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